École polytechnique de Louvain

The value of electric vehicles residential charging flexibility in short-term electricity markets

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Academic year 2023–2024
Master [120] in Electro-mechanical Engineering

Abstract

The energy transition is transforming our energy systems. Electricity supply has historically been the most widely used means of flexibility to ensure grid balance, with generation adapting to variations in demand. However, the growing share of Renewable Energy Sources (RES) in the electricity mix makes the supply-side less controllable, requiring the development of new means of flexibility.

On the other hand, the electrification of mobility is accelerating. While this represents a challenge for integrating this significant new demand in the grid functioning, it also represents an opportunity to leverage electric vehicles (EVs) charging in the network operations. Residential charging in particular is a suitable candidate to provide flexibility due to long connection time: the charge can be shifted in time without compromising user comfort. It nevertheless remains to be defined how to best exploit EV flexibility potential.

This work investigates the value that can be extracted from residential charging flexibility and more specifically the value of optimizing EVs residential charging in Belgian short-term electricity markets (Day-Ahead, Intraday and imbalance markets). The study is simulation-based: a virtual fleet of 2000 users is generated, where each user is attributed a yearly set of trips, EV and charger specifications and charging habits intended to represent a realistic Belgian fleet.

The fleet charges are optimized on a yearly basis, using historical prices of the year 2023 with the aim of minimizing the cost of recharging. Several strategies involving short-term markets are envisaged. Day-ahead optimization consists of completely redispatching the charges pattern to charge at the cheapest hours. Intraday and imbalance optimizations start from an existing charging plan and generate revenue by occasionally deviating from this plan within a charging session to stop the charge (resell electricity) and restart the charge (rebuy electricity) whenever there are interesting opportunities in these markets. Approaches coupling several markets in a single optimization strategy are also studied.

Results showed that smart charging in the day-ahead market enabled a significant cost reduction. Coupling the day-ahead optimization with participation in the imbalance market allows to generate additional income. Results also showed that intensive drivers generate the greatest revenue, with the number of kilometers travelled per year the most important factor influencing the unlocked flexibility. Sufficient nominal charging power is however required to fully exploit this flexibility, with greater charging power enabling more energy to be shifted at the right times. Results finally highlight the importance of the car availability in the generated revenue, demonstrating that more revenue could be generated if the car was more frequently plugged in.

Acknowledgements

My first thanks go to Professor Emmanuel De Jaeger for the trust he granted me throughout this academic year and for giving me the opportunity to carry out this work in collaboration with Laborelec.

I also wanted to thank Professor Francesco Contino and Gauthier de Maere d'Aertrycke for agreeing to be readers of this thesis.

I extend my thanks to Benjamin Pierre and Cathy Crunelle for their careful review and valuable advice, and especially to Benjamin for his wise and regular follow-up throughout the year.

I would like to express a special thanks to Arnaud Adam, who has been my greatest support throughout these 10 months of work. His availability, commitment and interest in my work, as well as the many discussions, advice and reviews, played a major role in its realization.

Thanks also to every single person at Laborelec and Engie in general who, whether directly or indirectly, helped me with their expertise and advice whenever I needed it.

Contents

Acronyms

aFRR automatic Frequency Restoration Reserve

BRPs Balance Responsible Parties

BSPs Balance Service Providers

DA Day-Ahead

DSO Distribution System Operator

EV Electric Vehicle

FCR Frequency Containment Reserve

ID Intraday

IEA International Energy Agency

MDP Marginal Decremental Price

mFRR manual Frequency Restoration Reserve

MIP Marginal Incremental Price

RES Renewable Energy Sources

SI System Imbalance

SoC State of Charge

TSO Transmission System Operator

V2G Vehicle-to-Grid

1 Introduction

The relationship between human activities and climate change is well established, and drastic, immediate, and global action is required to avoid global warming exceeding 1.5 or 2°C [1]. European Union aims to be carbon neutral by 2050 [2]. However, at present, 37% of European electricity production comes from fossil fuels. More globally, 70% of Europe's energy supply is still based on fossil fuels [3].

The transition of our energy systems towards decarbonized solutions is therefore a major challenge, and the electricity system in particular will face significant changes. Electricity supply and demand must be equal at all times, and it is historically the generation that adapts to meet uncontrolled demand. However, the growing share of Renewable Energy Sources (RES) in the electricity mix makes electricity production less controllable and poses a problem of grid balancing. Renewable electricity generation may sometimes exceed demand, leading to the curtailment of low-cost and carbon-free electricity. Inversely, in the case of low renewable generation, supply may not be able to meet demand. To keep the grid in balance, an action is thus required on the electricity demand to shift consumption when electricity is available [4].

On the other hand, the transportation sector must also face a transition towards decarbonized solutions and the European Union plans to ban Internal Combustion Engine vehicles by 2035 [5]. Electric vehicles (EVs) are part of the solution and, although it represents a challenge to integrate their consumption in the grid functioning, this is also an opportunity to leverage them in the network operations. EV charging is indeed relatively flexible: the charge can be shifted in time without compromising user comfort. Residential charging in particular appears to be a suitable candidate to provide flexibility, as EVs often remain connected to the charger for a longer time than needed.

The concepts of EV flexibility and smart charging are nevertheless relatively recent and it still remains to be defined how best to exploit EV flexibility potential.

This master thesis aims to assess the value that can be extracted from residential EV charging flexibility, and more specifically the value of optimizing EVs charging in Belgian short-term electricity markets (Day-Ahead, Intraday and imbalance markets).

The present work proposes first a model developed in the scope of an internship at Engie Laborelec preceding the thesis, that addresses the lack of real-world residential charging data by generating realistic trips and charging patterns. The modeled fleet charging is then optimized under different approaches. The value of mono-market optimization on each short-term market is first studied. The work also examines the possibility of a coupled strategy involving several markets in the same optimization.

The results of this work are intended to contribute firstly to identify the markets where EV flexibility can be exploited and the economic value that can be derived from it, and secondly to understand the characteristics of users (behavior or characteristics of EVs/chargers) that define their flexibility potential.

The report is organized as follows: flexibility in power systems, as well as a discussion on the flexibility potential of EVs are presented in Section 2. Section 3 describes power markets and ancillary services, discussing how EVs can participate and generate value in each market and justifying the selection of short-term markets for subsequent optimizations. Section 4 presents the assumptions and methodology used in the implementation of these optimizations. Section 5 presents, analyses and discusses the results while Section 6 finally concludes this report.

2 Context: Flexibility in power systems

This section provides a review of flexibility in power systems. Flexibility will first be discussed in a broad sense, with a general definition and a description of the flexibility requirements associated with the transformation of the electricity system. It will then be followed by a discussion on EVs flexibility potential.

2.1 General Overview

2.1.1 What is flexibility ?

In general terms, flexibility is defined as the ability to change or be changed easily according to the situation. In power systems, flexibility can be seen as the change in feed-in or withdrawal of an asset in response to an external signal [6]. Another flexibility definition proposed by the International Energy Agency is «*the extent to which a power system can modify electricity production or consumption in response to variability, expected or otherwise*» [7]. Variations in demand and generation must in fact be managed at all times to keep the system in balance through the use of controllable technologies. In its study *The power of flex (2023)*, the Belgian Transmission System Operator (TSO) Elia identifies a wide range of potential flexibility sources [8]. They can be grouped into the following categories:

- Supply-side flexibility: Production assets such as thermal generators are capable of adapting their production in a relatively short time frame.
- Storage: Storage assets are inherently flexible.
- Demand-side response: Consumers capable of adapting their consumption upon request.
- Interconnectors allowing to import or export electricity when needed.

Flexibility can be further described by the direction, as well as the reaction time and duration. Concerning the flexibility direction, an increased production or reduced consumption is referred to as upward flexibility, while a decreased production and increased consumption is referred to as downward flexibility. Elia distinguishes three types of flexibility regarding reaction time and duration:

- Slow flexibility which represents the ability to deal with expected variations in demand and generation in an intraday timeframe (up to a few hours ahead of delivery).
- Fast flexibility which can react within 15 minutes and represents the ability to deal with unexpected power deviation in real time.
- Ramping flexibility which is defined as a capacity which can react within 5 minutes and follow in real time the variations of production and consumption.

2.1.2 The flexibility needs

The energy transition is transforming our energy systems. Supply-side flexibility has historically been the most widely used means of flexibility, with the generation constantly adapting to demand. However, as the share of intermittent RES in the electricity mix is rising, electricity production is becoming less controllable. The combined effect of RES intermittency, fossil and nuclear phase-out, and the electrification of services such as transport and space heating is likely to induce tensions in the electricity system and requires the development of new means of flexibility.

In its study quantifying the adequacy and flexibility needs of Belgium for the period 2024-2034, Elia states that flexible consumption has the potential to flatten peak demand and manage the variability of RES. It is a necessary and important lever to make the energy transition efficient and affordable: in 2034, Elia estimates the gap, i.e. the new capacity to be found [1] (on top of existing and already contracted capacity) to ensure adequacy, at 3.9 GW. Not exploiting residential and industrial flexibility would further increase the need for additional capacity by up to 2.5 GW in Belgium by 2034. [9].

2.1.3 Demand-Side Flexibility

As stated just before, demand-side flexibility holds, according to Elia, the greatest untapped potential. Elia distinguishes two types of demand-side flexibility:

- **Implicit flexibility** which holds in the consumers' response to a price signal. Operators incentivize consumers to alter the timing of their consumption to reduce their electricity expenses. It can be realized through dynamic energy contracts with prices fluctuating according to the market and network conditions or capacity tariffs to reduce congestion. The value of implicit flexibility therefore lies in avoiding excessive costs.
- **Explicit flexibility** whose value lies in revenue generation, either through in-market active control or through contracted flexibility with TSO or Distribution System Operator (DSO), such as ancillary services. Exploiting residential assets in an explicit approach will require the development of new actors and technologies allowing decentralized assets to trade their flexibility on electricity markets. Markets functioning and opportunities can indeed be quite complex for end-consumers. New actors, called *Energy Service Providers* in Elia's flexibility study, are appearing in order to manage and steer the assets owned by consumers. The aggregation of multiple assets managed by one entity might allow end-consumers to access value streams that would not have been accessible otherwise. Indeed, accessing markets or services requires a certain minimum capacity, which can only be achieved for residential devices by aggregating and controlling them as a whole. This aggregation of decentralized assets controlled together is referred to as *Virtual Power Plant*.

Demand-side flexibility can be enabled through various means in the residential and tertiary sectors. In 2022, at Elia's request, the consulting company Delta-EE[2] studied the potential demand-side flexibility from residential and tertiary sectors in Belgium [10].

[1] 100% available/flexible
[2] now renamed LCP Delta

Delta EE identified factors allowing to determine the capability of assets to provide flexibility:

- Asset volume: Sufficient power and/or energy rating to be impactful.
- Asset flexibility: The capability of assets to deviate from the initial demand profile.
- Asset control: The capability to receive control signals and to respond appropriately.
- Appropriate metering: The ability to accurately measure the consumption of assets in timeframes relevant to flexible services.

Considering those enabling factors, Delta EE identified electric vehicles, heat pumps and home batteries as the most relevant residential assets for large-scale flexibility.

2.2 EV flexibility quantification

Due to their high energy demand and power rating, EV charging appears to be a suitable candidate to provide flexibility. Residential charging, in particular, seems relevant as EVs often remain connected to the charging point longer than needed, offering room for flexibility. This section provides a review of papers characterizing the flexibility potential of EVs and more specifically residential charging.

Sorensen et al. (2021) analyzed 6878 real charging sessions recorded in a housing cooperative in Trondheim, Norway from December 2018 to January 2020 [11]. Recorded data gave information such as the plug-in time, plug-out time and energy charged for each session. However, the charging power was unknown. Authors thus modelled the charging curve, assuming that the charge starts right after the connection and for two different assumed powers: 3.6 and 7.2 kW. A synthetic charging time is then calculated based on the known energy charged and the assumed charging power. To estimate the flexibility potential, two indicators were defined: the *non-charging idle time* and the *idle capacity*.

The idle time is computed for each session as the difference between the connection time and the charging time. The idle capacity is defined as the energy which could have been charged during the idle time. Those indicators thus represent how much and when the energy could have been shifted.

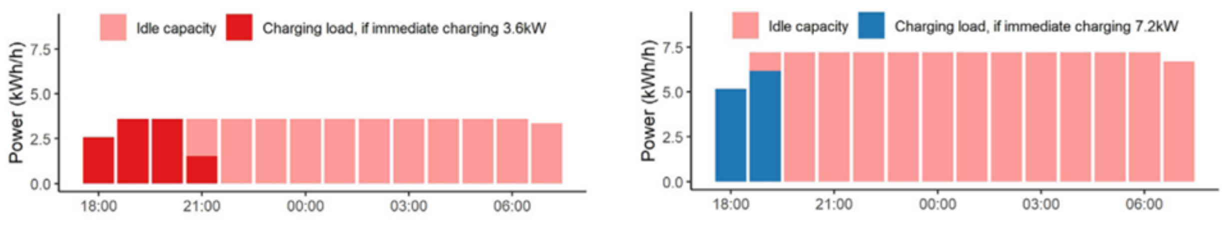


Figure 1: Charging load and idle capacity for a single charging session, assuming charging power of 3.6 (left) or 7.2 (right) kW ([11]). Energy charged and connection charged are the same but higher power gives higher idle capacity.

As illustrated in Figure 1 for a single charging session, it has been identified that for the same energy charged, higher charging power gives higher flexibility. For the aggregate charging of 17 users where 930 kWh were charged during one week, 3.6 kW charging gave 1200 kWh of idle capacity and 3100 kWh for 7.2 kW charging. Idle capacity was then multiplied by 2.6 between the 3.6 and 7.2kW case study, while the hourly aggregated charging peaks only increased by a factor of 1.2. Idle capacity, measured over the entire session, says nothing in itself about the amount of energy that could be shifted, since this is limited by the battery capacity. It does however indicate the moments the car is connected and not charging, and how much energy could have been charged at specific times. It has also been shown that idle capacity is the highest during the night and the weekend, meaning that there is a potential in shifting the charges in those periods.

Zhao et al. (2019) analyzed the flexibility of EVs charging based on data collected from 85 households owning EV in Texas, Colorado and California in a three-year period from 2015 to 2017 [12]. The authors studied EVs' ability to shift electricity consumption from peak to valley period by creating a dynamic price depending on the total electricity consumption in the area and creating a demand-response model optimizing the daily charging cost.

Authors demonstrated that the demand response optimization model effectively delayed EV charging to valley load period, with EVs charges starting in the late evening (9 to 10 pm) with a power peak occurring between 0 and 4 am, compared to standard charging where peak charging power occurred late afternoon (4 to 5 pm). This further confirms the possibility and interest in shifting the residential EV charges.

The Delta-EE study for Elia quantified the flexibility potential of EV charging in Belgium by 2035, based on forecasted EVs and charge-points growth [10]. Authors considered residential charging of electric passenger vehicles and workplace depot charging of electric Light Commercial Vehicles (eLCV). Public charging has not been considered, as drivers are likely to be connected for a short time or only connect if they really need to charge, leaving limited opportunities to shift the charging times. Authors did not consider either workplace employee EV charging. Although it is likely that high percentage of employee charging will be smart, the timing of the plug-in time (approx. 9 am to 5 pm) means according to the authors limited opportunity to shift demand to cheaper prices.

For the selected study cases, several EV operation modes were identified. The flexible operation mode depends first on the origin of the control signal, regrouped in two categories: local (denoted with the subscript H for House) signal and global (denoted with the subscript M for Market) signal. The former is related to home energy management. It can be linked to implicit flexibility with the aim of minimizing cost. In contrast, the latter is linked to explicit flexibility with the signal coming from an aggregator or a system operator with the aim of generating revenue. The operation mode also depends on the charger capabilities, with unidirectional charging denoted with subscript 1 and bi-directional charging denoted with subscript 2.

Overall, the following operation modes were identified:

- *V0 Natural charging*: EV charges as soon as plugged in.
- *V1H Delayed charging*: flatten the load based on local signals (minimizing peak load, consuming outside peak hours or maximizing PV self-consumption).
- *V1M Smart charging*: displace the energy consumption when it suits the market best.

- *V2H Vehicle-to-home*: optimize the charge based on local signals, with not only the aim to move consumption outside peak hours but also the possibility to reinject electricity back during those peak hours
- *V2M Vehicle-to-market or Vehicle-to-Grid*: dispatch the consumption when it suits the market best with the possibility to reinject electricity back into the grid.

Based on Elia's forecast of 2.6 million EVs in Belgium by 2035 and by comparing natural and optimized load profiles, the potential for energy shifting and peak load reduction of EV charging has been estimated. By 2035, Delta EE expects all residential charging to be smart, with 50% of V1H, 40% of V1M and 10% of residential chargers with bidirectional capabilities.

Concerning implicit flexibility (V1H and V2H), Delta-EE computed that EVs have the potential to shift up to 700 MW and 6 600 MWh/day away from peak periods by 2035. Until 2029, residential smart charging is the main driver of implicit flexibility. From 2030, bidirectional charging and eLCV flexibility are expected to grow rapidly.

Concerning explicit flexibility (V1M and V2M), Delta-EE expects that EVs could provide 900 MW of explicit flexibility by 2035, mainly with bidirectional charging.

The study also provides normalized results showing technical flexibility per 1000 installations on an average winter day (Table 1). V2G capabilities significantly increase EV flexibility potential, with energy shifting potential multiplied by a factor 2.5 and peak load reduction potential exploding.

	Daily Energy shifted [MWh/1000 vehicles.day]	**Max peak load reduction [MW/1000 vehicles]**
V1H	6.7	0.54
V2H	16.7	2.05
V2M	16.7	6.38

Table 1: Technical flexibility on an average winter day [10]. V2G capabilities significantly increase flexibility potential.

2.2.1 Vehicle-to-grid

The possibility to use EV batteries as power sources, referred to as vehicle-to-grid (V2G), vehicle-to-home (V2H), vehicle-to-building (V2B) or vehicle-to-everything (V2X) will then be key in unlocking the flexibility potential of EVs. However, at present, only a few vehicles are capable of V2G. Enabling V2X requires 4 things: a V2G-enabled vehicle, a bi-directional charger, an adapted communication protocol and a control system [13].

At present, there are a variety of charging standards around the world, but only the CHAdeMo protocol, developed by Japanese companies, has enabled V2G. Japanese brands such as Nissan are therefore leading most of the V2G trials that have taken place around the world [14]. The European/American CCS standard is currently enabling V2G, but the technology is not yet ready for widespread deployment.

As discussed in the previous section, Elia and Delta-EE estimate that the potential of V2G will be unlocked by 2028-2030, but expect only 10% of chargers with bidirectional capabilities by 2035.

Delta-EE considers that, due to the high cost of a bi-directional charger compared with a smart charger, it is extremely unlikely that customers would purchase a bidirectional chargepoint in the residential sector without already being set up for tariff optimization, i.e. having a smart meter and appropriate tariff.

In a V2G trial involving 320 V2G units in the UK between January 2020 and December 2020, a survey where participants were asked how likely they would be to purchase V2G hardware at a series of price points, only 20% of respondents were likely or highly likely to purchase the V2G hardware at the lowest price point tested of £3,000 to £3,500 (Figure 2, [15]). The cost of installed hardware within the trial was £4,700 plus VAT.

Considering those price limitations, V2G development in the residential sector is expected to be limited in the short term and V2G will not be discussed longer in this work.

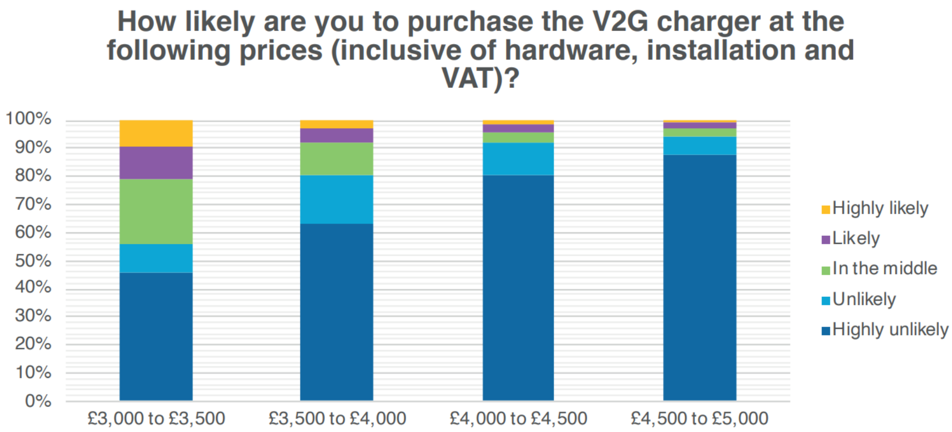


Figure 2: Results from Survey Question on Likelihood of Purchasing V2G Hardware [15]. The high initial capital cost of V2G hardware could be a barrier to the development of V2G in the residential sector.

3 Electricity Markets

Electricity trading can be operated in very different time horizons (Figure 3). This section provides an overview of the different markets and discusses the possibility of using the flexibility of EVs within these markets.

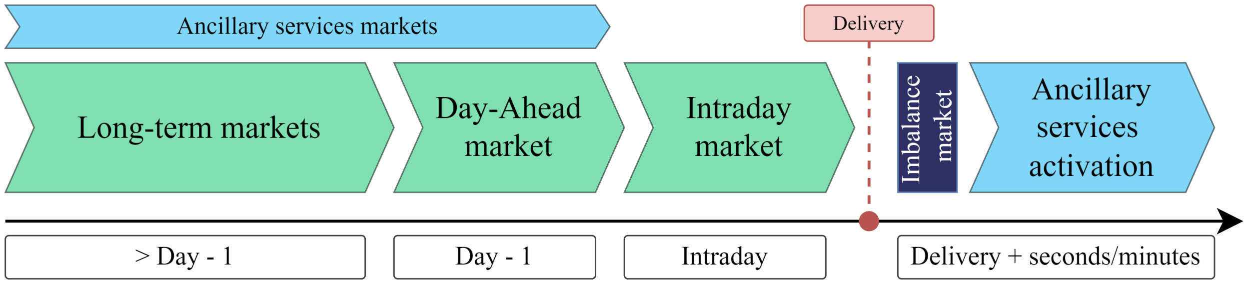


Figure 3: Electricity markets timeline. Long-term markets allow electricity to be purchased days, weeks, months or years in advance of delivery. The day-ahead market is a daily auction market where every day at noon, hourly blocks are bought and sold for the next 24 hours. Intraday market allows to adapt positions up to 5 minutes before delivery. After the delivery, the action of the imbalance market and ancillary services ensures the grid equilibrium.

3.1 Long term markets

In long-term markets, electricity is purchased now for later consumption. Electricity can be delivered in days, weeks, months, quarters or years ahead, at a price fixed on the date the contract is concluded. It allows buying electricity at a fixed price to hedge against (possibly high) fluctuation in short-term electricity prices [16, 17]. It is also a way for electricity producers to secure a certain revenue. Long-term markets can be divided into two families:

- Forward markets: long-term forward or futures contracts can be exchanged on the ICE Endex (European Energy Derivatives Exchange) and EEX (European Energy Exchange) platforms. A multitude of delivery periods are offered: one to several months ahead, one to several quarters ahead and one to several years ahead. It allows producers to sell electricity upstream of production and therefore finance capital expenditure. It also enables big consumers such as industrials to secure a baseload at a fixed price.
- Over-the-counter (OTC) contracts that are bilateral transactions between a producer and a consumer, without necessarily entering a market. Typical OTC contracts are Power Purchase Agreements (PPAs), which are deals between a producer and an off-taker to buy the output of a certain production unit. Green PPAs become popular with the growing of renewable production units and make it possible for instance to buy the output of a windmill at a fixed price for a given period.

Flexibility is the ability to adapt production or consumption quickly in response to an external signal. It is therefore a concept inherently linked to a short-term time window and can hardly be exploited in long-term markets. We could, however, imagine using the flexibility of EV charging by purchasing long-term load profiles at times when we know it would be beneficial for the grid (for example in the afternoon when there is a large solar production or during the night to avoid the evening consumption peak). Nevertheless, the intrinsic uncertainty in renewable production and user behavior will in any case require action on short-term markets. Long-term markets will therefore not be discussed further in this work.

3.2 Day-ahead market

3.2.1 Market principle

The more we approach the actual delivery of electricity, the more forecasts about consumption and renewable production become accurate. The day-ahead (DA) market is the first opportunity for buyers and sellers to adapt their positions. It is an auction market where every day at noon, hourly blocks are bought and sold for the next 24 hours.

In the DA market, each participant submits their bid for the next 24 hours, in price and volume, before the gate closure at noon. After the gate closure, the Power Exchange platforms rank the auctions by price and volume and establish a buy and a sell curve for each hour. A schematic example is represented in Figure 4. For each hour, the Market Clearing Price (MCP) is computed as the price at the intersection of both curves. This kind of market is called paid as clear: each participant whose bid is accepted pays or receives the MCP. As generation bids are sorted in ascending order, it is the price of the last activated unit required to match demand that defines the MCP. This is referred to as the merit order curve principle.

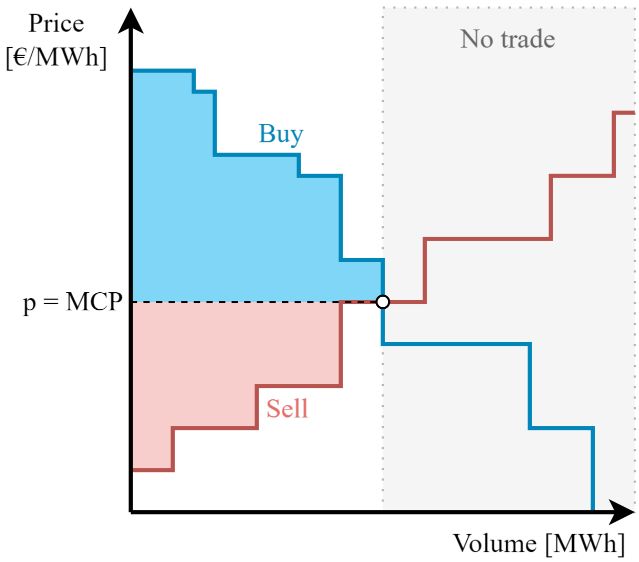


Figure 4: Day-Ahead Market clearing principle. Sell and buy auctions are ranked in price and volume, the Market Clearing Price (MCP) is the price at the intersection of both curves. All cleared participants pay/receive the MCP.

With the increasing penetration of RES in the electricity mix, the DA market has become increasingly important as the inherent variability of RES and forecast errors require more close-to-delivery adjustments. In 2022, the total volume exchanged in the day-ahead market in Belgium was 22.1 TWh, i.e. just over a quarter of the Belgian electricity consumption (81.7 TWh). It represents an increase of 21% compared to 2021 [16].

3.2.2 EV participation in the Day-Ahead market

Figure 5 shows the average cleared prices in the Belgian DA market for the year 2023. It can be observed that for weekdays, prices are on average 40% higher during the evening (between 5 pm and 11 pm) than during the night (between midnight and 6 am). We also observe the lowest prices during the weekend. On the other hand, in a scenario where people would charge in an uncontrolled manner, i.e. directly charging when plugging in, EVs would charge mainly in the evening, at the moment demand is already high and DA prices are at their peak. As EVs are a priori connected all night when plugged-in in the evening, it is possible to avoid high costs by scheduling the charges so that it takes place during the cheapest hours.

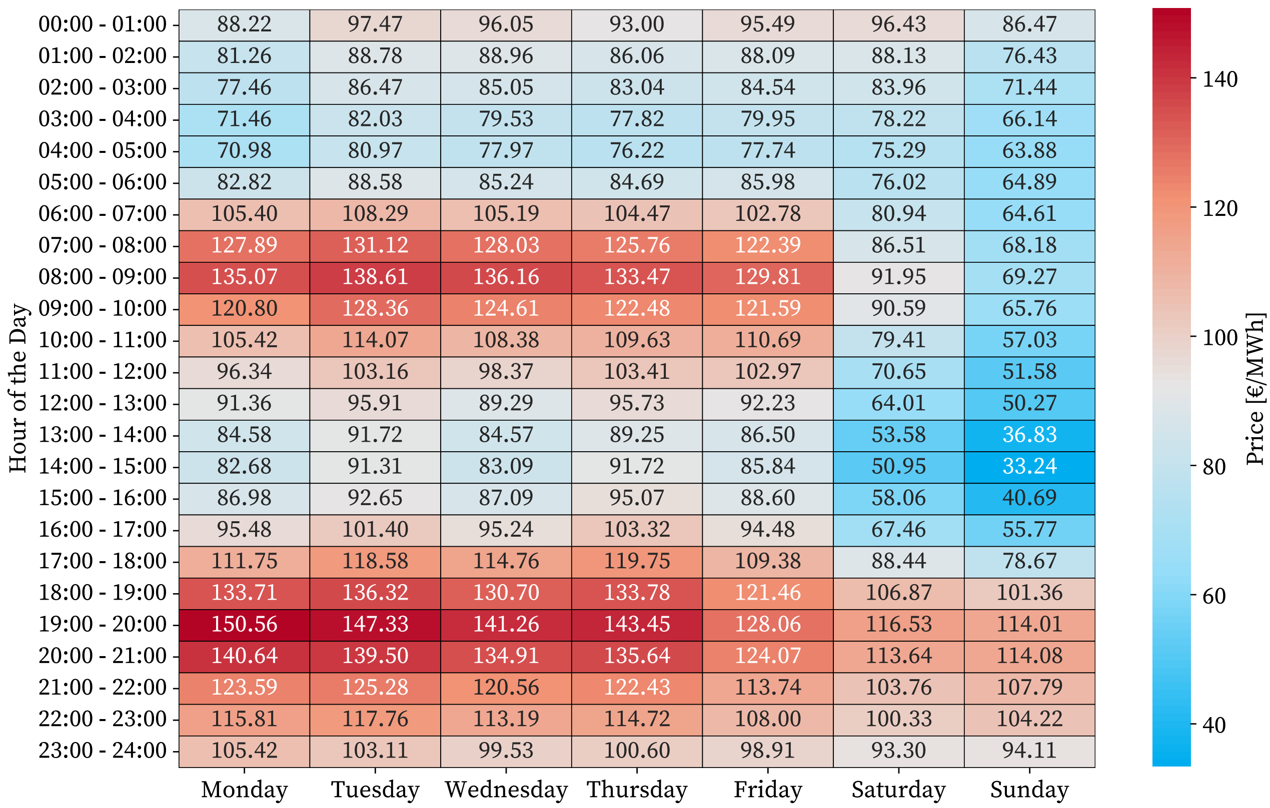


Figure 5: Average day-ahead prices for the year 2023 [€/MWh]. Typical patterns can be observed such as weekday morning and evening peaks or low prices in the weekend.

3.3 Intraday market

3.3.1 Market principle

Sellers have the obligation to declare all their volume in DA, but we see in Figure 4 that there are some unmatched deals (at the right of the intersection). Moreover, unforeseen events, such as the failure of a production unit, can still occur after day-ahead clearing. If a generating unit is no longer able to deliver electricity, but its output has already been sold, the producer must buy back electricity to honor its contract. The intraday (ID) market allows to adapt positions after the clearing of the day-ahead and to buy or sell electricity up to 5 minutes before real delivery.

In DA, there is only one price that exists after the clearing. Intraday is rather a continuous market. The ID transactions are said paid-as-bid: prices are set based on each transaction that is executed. As represented in Figure 6, we then have two price curves (the buying and the selling curve), coming from the DA unmatched deals and continuously evolving. There is a clearing only if the two prices intersect (meaning that a buyer or a seller has changed their position to agree on a price and volume).

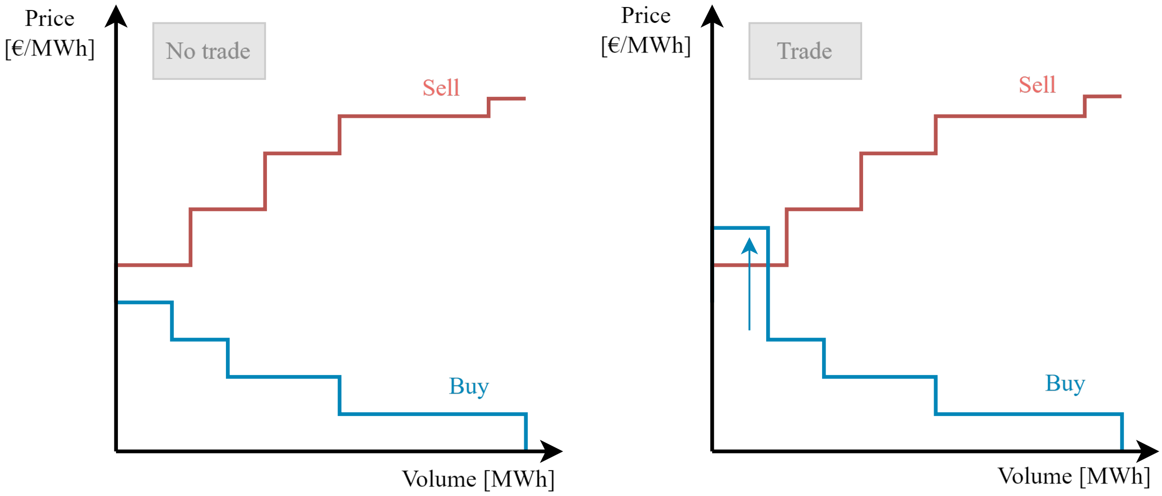


Figure 6: In intraday, there are two price curves coming from unmatched day-ahead deals. There is a deal only if the two curves intersect, meaning that the buyer of the seller has changed its position.

Intraday allows actors to make last-minute adjustments and to balance their portfolio closer to real-time. This opportunity is becoming increasingly relevant with the growing share of intermittent renewable energy sources: in Belgium, energy exchanged in ID increased from 2.9 TWh in 2021 to 4.4 TWh in 2022 [16].

3.3.2 EV participation in the intraday market

As explained above, transactions are paid-as-bid and there is therefore no unique price for all transactions executed at a given time. It is consequently not possible to find unique hourly historical price data that could be used in simulations, as is the case for DA.

Trading platforms nevertheless calculate indices providing information on the market price [18]:

- ID1 index: weighted average price[3] of all continuous trades executed within the last trading hour before delivery.
- ID3 index: weighted average price of all continuous trades executed within the last 3 hours before delivery.
- IDFull index: weighted average price of all continuous trades executed during the full trading session.

ID1 index therefore represents the most price variability that could occur in intraday, since the longer time window for calculating the weighted average makes the average smoother. It is the index that has been selected for simulations.

[3] Intraday trades are settled in price and volume, ID indices represents the volume weighted average of all trade executed in the specified window

Figure 7 shows the comparison between ID1 index and DA prices on specific days. It can be noticed that, as ID transactions come from DA deals that have not been concluded, the intraday price fluctuates around the day-ahead price. For the ID market to be advantageous in an optimized EV charging strategy compared to a DA optimization, the car should be charged during the sharp falls of intraday prices, meaning that a producer, for example with a surplus of renewables production, is keen to sell its electricity at a very low price.

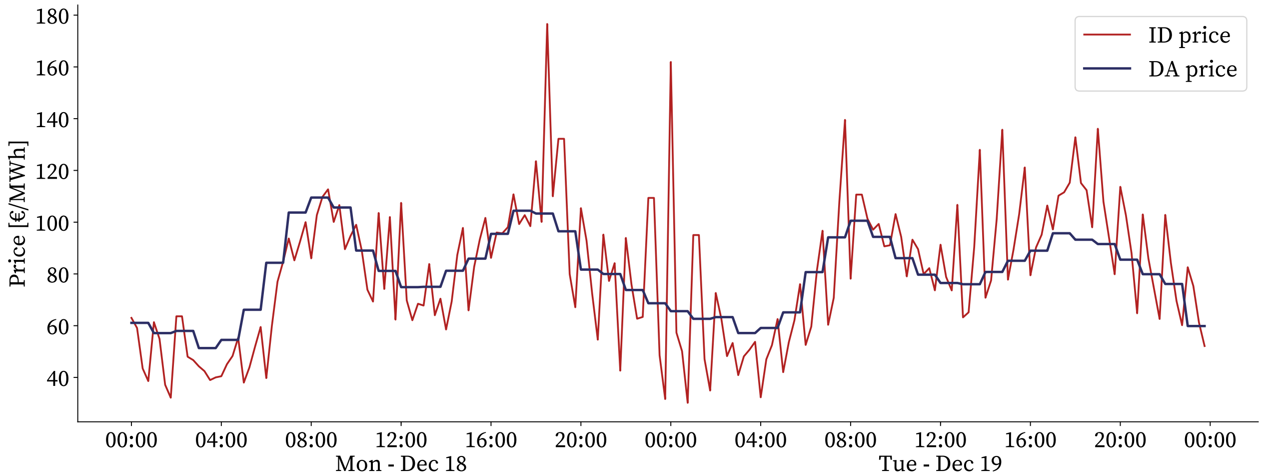


Figure 7: Comparison between the ID1 index and day-ahead prices on 18 and 19 December 2023. ID prices fluctuate around DA prices, with occasional sharp rises and falls.

Given that these periods are hardly predictable, it seems complicated to formulate a charging plan solely based on intraday. However, the ID market could be occasionally used to adapt the position compared to a DA charging plan to take advantage of the sharp rises and fall in the ID prices. Once the charging pattern is bought and secured in DA, value can be generated by stopping the charge and reselling the electricity at a high ID price. On the other hand, one could also generate value by charging at a low ID price, when it was not planned to charge in the initial DA plan.

It is worth noting that EVs have a finite amount of energy to charge, defined by the number of kilometers travelled by their users. It means that if we decide to deviate from the DA plan to benefit from an opportunity in ID, such as stopping the charge, the energy that has not been charged will have to be retrieved later. From this perspective, the ID market could also be used in a cross-market optimization strategy, for instance to rebuy electricity after taking an action in another market. This will be further discussed in subsection 3.4.3.

3.4 Imbalance market

3.4.1 Market principle

After the gate closure of financial markets, unforeseen events such as unplanned production shortfall or an unexpected variation in demand can still occur and disrupt the balance between electricity production and consumption [19]. The growing share of renewables further increases this risk of imbalance: Elia, the Belgian TSO, monitors 5.3 GW of wind turbines. Even with the most accurate forecasts, variation of more than 500MW between the forecasted and the realized production is possible and must be managed [20].

The balance of the whole system is the responsibility of the TSO, but it relies on the help of Balance Responsible Parties (BRPs). BRPs are private legal entities managing a portfolio of generation/consumption assets and responsible for the balance of their portfolio [21]. Each injector or off-taker in the grid is obliged to have a contract with a BRP or can be their own BRP.

The BRPs must remain balanced on a quarter-hourly basis, but real-time imbalances can still occur. It is the TSO's responsibility to activate the ancillary services to deal with the real-time imbalance and the residual imbalance that BRPs have not been able to manage.

In order to incentivize BRPs to remain in balance, TSOs apply a financial penalty, hereafter referred to as the "*imbalance price*", to BRPs that deviate from their own equilibrium. In function of the sign of the BRP's imbalance and the sign of the imbalance price, BRPs either receive or pay the imbalance price to the TSO.

	Imbalance price positive	**Imbalance price negative**
BRP in positive imbalance	Payment from TSO to BRP	Payment from BRP to TSO
BRP in negative imbalance	Payment from BRP to TSO	Payment from TSO to BRP

Table 2: Possible cases for financial flows (adapted from Tariffs déséquilibre 2024-2027 - Elia [22])

Table 2 shows the different possible cases for financial flows. A positive imbalance corresponds to an excess in production (or a lack in consumption) while a negative imbalance corresponds to an insufficient injection (or an excess in consumption). The sign of the BRP's imbalance determines whether it receives or is charged the imbalance price. This imbalance price is generally positive. In this case, a BRP with a positive imbalance gets its excess energy bought by the TSO at the imbalance price. In contrast, a BRP facing a negative imbalance will have to pay the imbalance price to the TSO for the energy shortage. However, the imbalance price can sometimes be negative, resulting in reverse payments between the TSO and BRPs [22]. The method for pricing imbalances and the reason for the negative price will be further discussed below.

BRPs must then deploy all reasonable resources to remain in balance on a quarter-hourly basis. However, in Belgium, BRPs are authorized to deliberately deviate from their balance if it helps to restore the balance of the overall system [23]. It is therefore important to note that what is abusively called the imbalance market is not strictly speaking a market but rather a penalty system where one is fined if they deviate from their plan. However, if the deviation helps the system to restore equilibrium, the fine can be negative and thereby turn into a remuneration.

3.4.2 Pricing method

At each quarter-hour, Elia calculates and publishes the System Imbalance (SI), i.e. the total disequilibrium between injection and consumption in the area. The imbalance price is computed afterwards as it depends on the cost of activating ancillary services. The imbalance price is in fact computed according to Table 3, where:

- MIP (Marginal Incremental Price) is the marginal price of upward reserve activation, i.e. the highest price of energy requested by Elia to resorb negative system imbalance. MIP is defined as positive for a transaction from Elia to BRPs.
- MDP (Marginal Decremental Price) is the marginal price of downward activation, i.e. the lowest price received by Elia for downward regulation to compensate for the positive system imbalance. MDP is defined as positive for a transaction from BRPs to Elia.
- α represents an additional incentive that increases exponentially for imbalance above 150 MW to encourage BRPs to act in case of large imbalance.

<table>
<tr><td></td><td></td><td colspan="2">System imbalance</td></tr>
<tr><td></td><td></td><td>Positive</td><td>Negative or zero</td></tr>
<tr><td rowspan="2">BRP imbalance</td><td>Positive</td><td rowspan="2">MDP - α</td><td rowspan="2">MIP + α</td></tr>
<tr><td>Negative</td></tr>
</table>

Table 3: Imbalance pricing method (adapted from [22])

If the SI is negative (shortage of energy), Elia compensates for the system imbalance by activating reserve capacity from Balance Service Providers (BSP). Elia charges BRPs in negative imbalance (thus aggravating the SI) with MIP + α and remunerates BRPs in positive imbalance (thus helping the SI) with the same MIP + α.

If the SI is positive (surplus of energy), Elia compensates by activating downward reserve. Taking the same logic as for negative imbalance, BRPs aggravating the imbalance should be fined and BRPs helping to resorb the imbalance should be remunerated. With the convention defined in Table 2, this would result in negative imbalance prices: BRPs get paid to produce less and must pay to produce. However, as mentioned earlier, this situation is quite rare, because BSPs are often willing to pay Elia to be activated, reversing the price logic [19].

BSPs providing ancillary services such as automatic Frequency Restoration Reserve (ancillary services will be further discussed in subsection 3.4.4) are paid for both reservation and activation: a first auction determines the designed reserves that must be ready to be activated and a second auction takes place between the reserved players, determining who will be selected for activation according to a merit order curve. As for a generation unit, participating in downward regulation means reducing the power output and thus saving operating costs, generators such as CCGTs are usually keen to make negative bids (i.e. pay to be activated) up to the amount representing the saved operating costs. In this case, imbalance prices are positive and BRPs that are in a positive imbalance are paid MDP - α for the excess energy produced. They are thus paid even though they are worsening the imbalance, but they are on average paid less than if they had sold this electricity on conventional markets.

On the other hand, when the MDP is negative, the imbalance price is negative, giving rise to an unnatural situation where one is paid to consume more and has to pay to produce. This situation is actually infrequent in Belgium: In 2022, the SI was positive 44% of the time while imbalance price was negative 12.9% of the time.

	SI <= 0 and €>=0	SI >0 and €>= 0	SI >0 and €<0
% of occurrences in 2022	56.1%	31.0%	12.9%

Table 4: System imbalance (SI) and imbalance price sign in 2022. Negative imbalance price is quite infrequent and occurs only when downward flexibility is rare.

A negative MDP means that BSPs providing ancillary services made positive bids, which only occurs when downward flexibility is rare. This happens in particular situations such as the simultaneous occurrence of high RES generation and low demand because RES have no incentive to reduce their output as their production cost is nearly null, at the opposite of CCGTs. Generators such as CCGTs may also bid positive activation prices if the downward activation results in a shutdown, which is not desirable due to start-up delay and cost.

3.4.3 EV participation in the imbalance market

As explained before, imbalance prices result from unforeseen events creating an imbalance between generation and consumption and are thus inherently unpredictable and volatile. As for the ID market, those characteristics do not allow to envisage a charging plan solely based on imbalance. One could however take advantage of the high price volatility to adapt the DA plan by stopping or beginning a charge when it was not initially planned.

When the SI is negative (shortage of energy), value can be generated by stopping the charge of vehicles that were planned to charge. As the energy is already bought in conventional markets, this is equivalent to reselling this energy at the imbalance price. As already mentioned in the intraday subsection 3.3.2, EVs have a primal function - transporting their users - and therefore a finite amount of energy to charge. It means that if we take action on the imbalance market, such as stopping the charge, the energy that has not been charged will have to be retrieved later.

The missing energy can be retrieved by creating an imbalance in the other direction at another moment (i.e. charging the vehicle when it was not planned to charge). To be consistent with the system needs, starting a charge should occur when the SI is positive. As discussed before, when facing positive SI, the imbalance price can either be positive or negative. However, the positive prices for positive imbalances are generally lower than in the case of negative imbalances. As shown in Figure 8, the price when negative SI is generally greater (median price was 338.73 €/MWh in 2022), than the price when positive SI (median price was 70.00 €/MWh in 2022). Selling electricity in case of negative SI and rebuying it when facing positive SI would then give rise to a financial gain.

On the other hand, when a charge is stopped to take advantage of an attractive imbalance price, the electricity that has not been charged must be recovered, but you still have until the end of the charging session to do so. Instead of waiting for an opportunity to restart a charge by creating an imbalance in the other direction, one could think of taking advantage of the ID price volatility to buy back the missing energy. This option will also be studied in the following of this work.

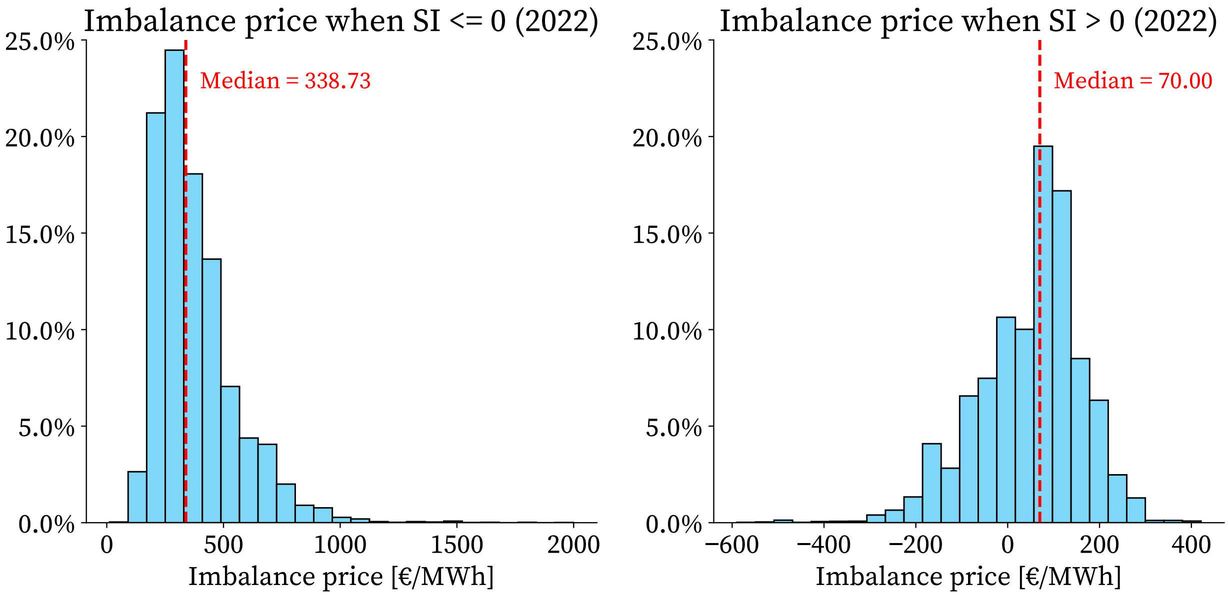


Figure 8: Imbalance prices in 2022. The price for negative imbalance is overall greater than the price for positive imbalance.

3.4.4 Ancillary services

As explained before, it is the responsibility of the TSO to keep the system in balance. This balance is essential to ensure that the grid operates correctly at the required constant frequency of 50 Hz. When unexpected fluctuations result in an imbalance between injected and consumed energy, the TSO activates control reserves to restore the balance by adjusting generation or consumption upwards or downwards. Frequency control is provided by Balancing Service Providers (BSPs) and is referred to as ancillary services, together with other system services such as voltage or reactive power control or the black start service.

Frequency control services are divided according to the timescale at which they operate, as depicted in Figure 9. Frequency Containment Reserve (FCR) is the first activated service after a sudden change in generation or production. It has to react automatically and almost instantaneously to frequency variations, preventing it from deviating too far from its nominal value. FCR providers activate the service in a few seconds and must be fully deployed within 30 seconds. Once activated, FCR provider must continuously adapt their production/consumption proportionally to frequency deviations measured from local frequency meters [24].

FCR aims to contain the frequency deviation to an acceptable range. The automatic Frequency Restoration Reserve (aFRR) then takes over to restore the frequency to its nominal value. aFRR is automatically activated after 30 seconds of frequency deviation and must be fully activated within 5 minutes. Once activated, aFRR provider must be able to automatically adapt its output based on set-points sent every 4 seconds by the TSO [25].

Finally, in case of significant or persistent imbalance that previous services have not been able to manage, manual Frequency Restoration Reserve (mFRR) is manually activated by the TSO to support or gradually replace aFRR. It must be available within 12.5 minutes [26].

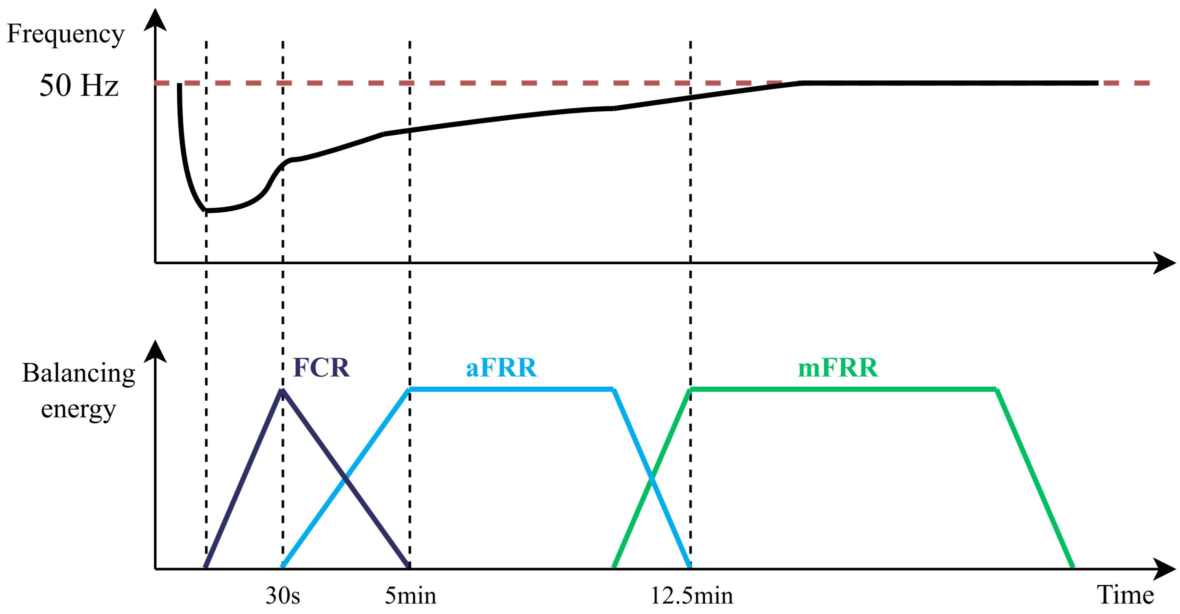


Figure 9: Frequency control activation. Frequency Containment Reserve (FCR) is activated after a sudden frequency variation to prevent it from deviating too far from its nominal value. The automatic Frequency Restoration Reserve (aFRR) then takes over to restore the nominal frequency. In case of large or persistent imbalance, manual Frequency Restoration Reserve (mFRR) is activated to support or replace aFRR.

In the scope of this work, it has been decided to not act in ancillary services with EV residential charging. The following paragraphs justify further this choice.

Firstly, participation in FCR requires local frequency measurement which adds an implementation difficulty while managing a fleet of residential chargers spread geographically across Belgium. It also represents an additional hardware cost, which can be a barrier if the purchase is at the customer's expense.

Moreover, EVs are not the only decentralized assets that can provide flexibility. Large-scale battery storages, with short response times and high power ratings, are suitable to provide ancillary services. In Germany, FCR prices have fallen significantly in recent years with the increased participation of batteries (before rising again in 2022 due to the energy crisis). In early 2023, 630 MW of batteries were prequalified for FCR in Germany with a market size of 570 MW [27]. The market could therefore rapidly be saturated.

In Belgium, large-scale battery capacity is expected to grow rapidly: Engie plans to install 380MW of batteries in Belgium by 2025 [28], and other large-scale projects are on the way [29, 30].

Concerning aFRR and mFRR, the current harmonization of the markets at the European scale facilitates the cross-border exchange of balancing energy and has the declared aim of bringing effective competition, non-discrimination and transparency to balancing markets [31, 32].

In conclusion, the value of flexibility for decentralized assets in ancillary services is more difficult to access than in conventional markets, firstly due to high requirements standards and secondly because of increased competition. This concurrence is driven by the rise of large-scale batteries and other decentralized assets capable of providing flexibility, as well as European harmonization. Ancillary services seem less suited for EVs than other systems such as large batteries offering the same service with a single access point to monitor.

Aggregators such as Nextkraftwerke or Flexcity nevertheless proved that pools of small decentralized assets were able to meet the technical requirements and to deliver aFRR service with sufficient accuracy [33, 34]. There is thus some potential but in the scope of this work, it has been decided to focus on short-term markets carrying more value and more easily accessible for decentralized assets.

4 Methodology

This work aims to study the flexibility potential that can be extracted from optimizing residential EV charging on short-term markets (Day-Ahead, Intraday and Imbalance), first in a mono-market approach and then in a coupled strategy. This section provides all assumptions and describes the methodology used in the implementation of these optimizations. Figure 10 depicts the methodology structure.

The model is simulation-based: a virtual EV fleet is first created based on probabilistically determined characteristics such as user set of trips, EV and charger specifications and user charging habits. Simulations are operated on a yearly horizon with quarter-hourly timesteps. The trips generator creates for each user a yearly set of trips, based on which the charge generator generates the charges allowing to fulfill the trips demand. In the natural charge case, charges are uncontrolled, i.e. start directly when the car is plugged in and continue until the car is fully charged. In the optimized charge cases, charges are optimized in order to minimize the charging cost according to the chosen markets and strategies. The optimization gain is finally computed as the difference between the cost of charge in the natural case and the cost of charge in the optimized case.

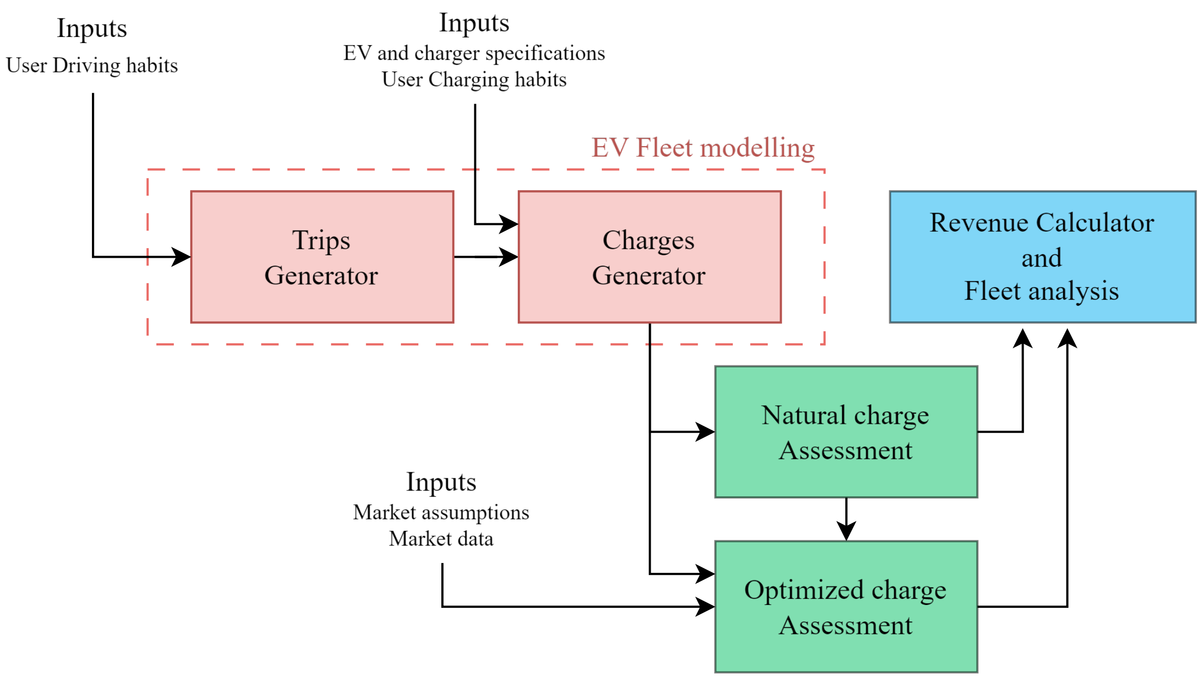


Figure 10: Schematic of the methodology

Subsection 4.1 presents the EV fleet modelling as well as the natural charge assessment. Subsection 4.2 details the implementation of the different optimizations. Subsection 4.3 describes how the revenue of each optimization has been computed while subsection 4.4 details the input data used in the model. Subsection 4.5 finally presents the tools used for analyzing the results.

4.1 EV fleet and natural charge modelling

Studying EV flexibility requires a good understanding of driving and charging behaviors. However, residential charging is still relatively unknown, and we lack real charging data in Belgium. In the scope of an internship preceding the thesis, I have implemented a model of residential charging in Belgium that addresses the lack of real-world residential charging data by generating realistic trips and charging patterns. This part is not the main point of interest of the thesis but nevertheless represents an important input for this work. This section summarizes the important key points of the model I realized and the complete report is available in Appendix A.

4.1.1 Method

The model is based on statistical inputs to generate a set of profiles that is representative of the situation in Belgium. It has been built following the steps explained hereafter.

Firstly, for each user, a list of all trips made over the year is generated with departure time, arrival time and distance travelled. Trips are generated based on:

- The Monitor Survey [35], the last major mobility survey in Belgium, which provides statistical data on departure and arrival times, distance travelled or the reason for journeys.
- Teleworking statistics [36], that influence the use of car for commuting.
- The average annual mileage of EV users, which is 15% higher than the global average in Belgium [37]
- Variation of traffic due to holidays.

Based on those inputs, the model returns for each user a list of all trips of the year with departure time, arrival time and distance travelled. Charges are then generated to fulfill the trip demand following a certain behavior. Two uncontrolled behaviors[4] have been identified and used in other models [38] [39]:

- *Top-up charging*: user always starts charging when back home, regardless of the battery state of charge.
- *Soc charging*: user only starts charging when back home if the State of Charge (SoC) is beneath a certain threshold.

In accordance with literature and manufacturer's advice, batteries are charged up to 80% to extend their lifetime [40], but it is allowed to occasionally charge to 100% if it is necessary for the next trip.

[4]the charge starts right after the user connects the EV to the charger

The effect of ambient temperature on electrical consumption, which is not negligible [41, 42], has been considered. The minimal consumption is around 20°C and increases as we move away from this temperature both with warmer and colder temperatures, mainly due to the consumption of auxiliaries such as air conditioning or heating. This variation was considered by applying a factor to the consumption depending on the outside temperature while driving.

4.1.2 EV and chargers' characteristics

As EVs do not yet represent a significant proportion of vehicles in Belgium, it is difficult to obtain information on the composition of the EV fleet. Based on top sales from recent years [43, 44, 45], Table 12 shows how the fleet has been divided, according to battery capacity (low, medium, long and very long range) and electricity consumption (berlines and SUV). The electricity consumption indicated in the table is the consumption at optimal conditions (temperature of 20°C and no use of air conditioning [46]).

<table>
<tr><th colspan="2">Category</th><th>Consumption
[Wh/km]</th><th>Battery capacity
[kWh]</th><th>Proportion</th></tr>
<tr><td colspan="2">Low range</td><td>140</td><td>39</td><td>20%</td></tr>
<tr><td colspan="2">Mid range</td><td>140</td><td>57.5</td><td>30%</td></tr>
<tr><td rowspan="2">Long range</td><td>SUV</td><td>165</td><td rowspan="2">75</td><td>20%</td></tr>
<tr><td>Berlines</td><td>140</td><td>20%</td></tr>
<tr><td rowspan="2">Very long range</td><td>SUV</td><td>175</td><td rowspan="2">95</td><td>5%</td></tr>
<tr><td>Berlines</td><td>140</td><td>5%</td></tr>
</table>

Table 5: EV fleet distribution. Each time a user is created, it is assigned to a category according to the probabilities indicated in the Proportion column and the corresponding parameters are assigned to it.

Concerning the charging points, no information about the nominal power of residential charging points has been found for Belgium. The assumed distribution is shown in Table 13. A charging efficiency of 90% is assumed, and no power modulation is considered for the uncontrolled charging case (the charger always works at its nominal power).

Charging power [kW]	3.6	7.4	11	22
Proportion [%]	30%	50%	10%	10%

Table 6: Charging power distribution.

4.1.3 Model outputs

I constituted a virtual fleet of 2000 users and generated for each the yearly charging pattern. The yearly energy demand of the simulated fleet is on average 2600 kWh per user. This consumption shows a great variation between summer and winter months, as depicted in Figure 11, due to the combined effect of holidays and consumption variation with temperature. 72% more energy is charged during January and December compared to July and Augustus.

Figure 12 shows the aggregated weekly demand, normalized by the number of users. The peak consumption appears when people return from work and the total demand is substantially reduced during weekends.

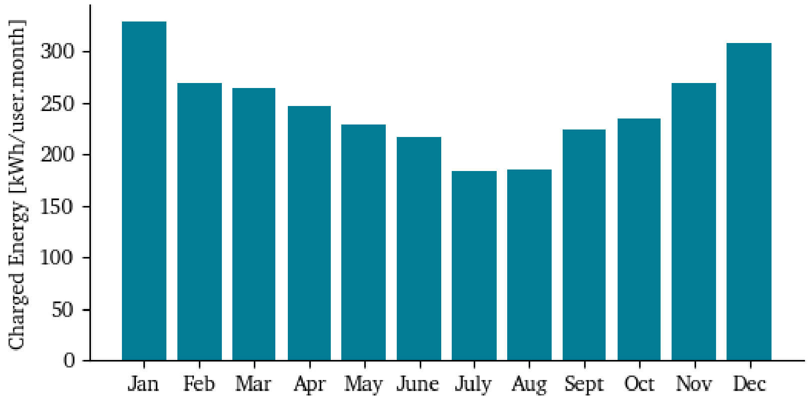


Figure 11: Charging energy demand by month. 72% more energy is charged during January and December compared to July and Augustus.

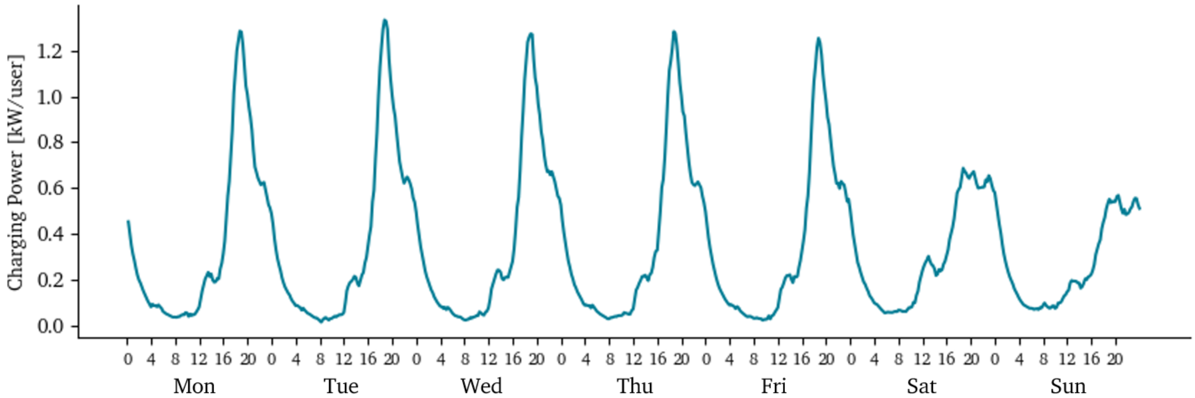


Figure 12: Weekly demand profile. The power demand reaches a peak in the early evening and rapidly decreases in the night to reach the lowest point in the morning. Demand is substantially reduced during weekends.

4.1.4 Comparison with real data

At the moment of the realization of this model, no data were available for Belgium. Results have thus been compared to a study analyzing real charging sessions in Norway and providing all the used datasets online. *Sorensen et al. (2021)* analyzed 6878 real charging sessions recorded in a housing cooperative in Trondheim, Norway from December 2018 to January 2020 [11]. Recorded data gave information such as the plug-in time, plug-out time and energy charged for each session allowing an in-depth analysis of the charging sessions.

Different metrics have been defined to compare the simulation fleet to the Norwegian data:

- The average amount of kilowatt-hours charged per session, as well as the standard deviation.
- The average amount of kilowatt-hours charged per week.
- The number of charges per week.
- The percentage of charges starting on a weekday, Saturday or Sunday.
- The percentage of charge starting at night (0 am to 6 am), in the morning (6 am to noon), in the early afternoon (noon to 3 pm), in the late afternoon (3 pm to 6 pm) and in the evening (6 pm to midnight).

Table 7 compares those metrics for both the Norwegian data and simulation results. It can be observed that the simulation results are fairly consistent with the Norwegian data. The only notable difference concerns the amount of energy charged per session and per week, which is higher in the simulation as we ride 50% more km in Belgium than in Norway [37, 47].

	Norway study	Simulation
Avg kWh/charge	11.61 kWh	15.20 kWh
Std KWh/charge	0.47	0.57
Avg kWh/week	42.71 kWh	50.20 kWh
N_charge/week	3.65	3.30
% charge_weekday	73.65%	74.11%
% charge_saturday	11.81%	14.24%
% charge_sunday	14.54%	11.65%
% charge_night	2.3%	1.20%
% charge_morning	6.9%	6.63%
% charge_early_aft	13.45%	10.07%
% charge_late_aft	34.6%	34.52%
% charge_evening	42.6%	46.57%

Table 7: Comparison between real Norwegian data and simulation results.

Figures 13, 14, 15 and 16 depict histograms displaying the distribution of plug-in and plug-out times throughout the day, for both weekdays and weekends, as well as for both the Norwegian data and the simulation results. The simulation results exhibit similar patterns to those observed in the Norwegian data, in both shape and magnitude. As expected, there is a high peak of plug-out in the morning when people leave for work, and a high peak of plug-in when they return home from work.

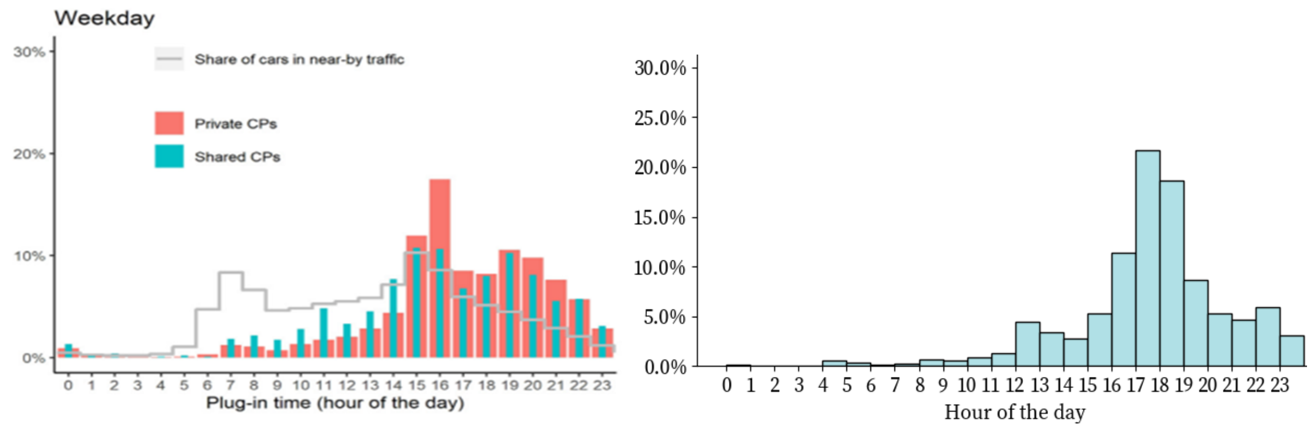


Figure 13: Distribution of plug-in times - Weekday for Norwegian data [11] (left) and simulation results (right).

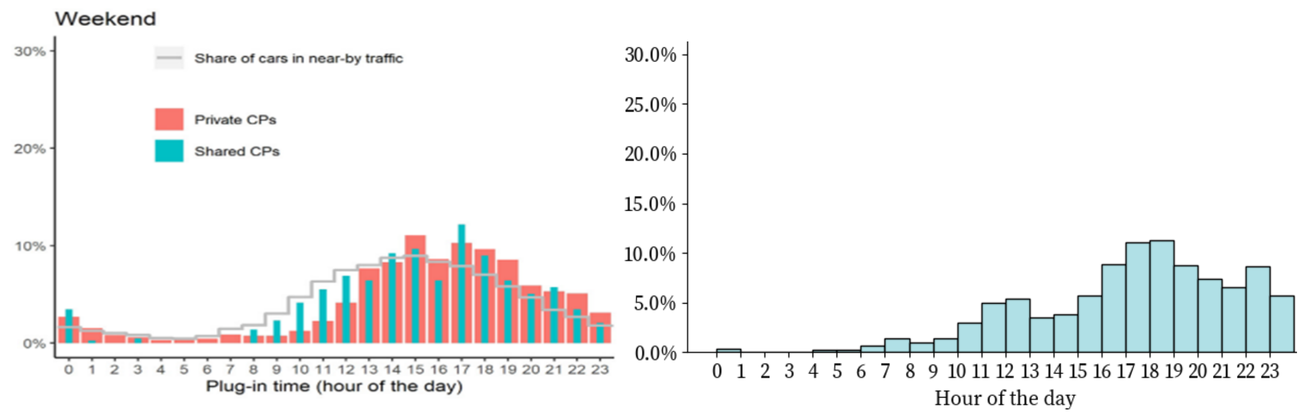


Figure 14: Distribution of plug-in times - Weekend for Norwegian data [11] (left) and simulation results (right).

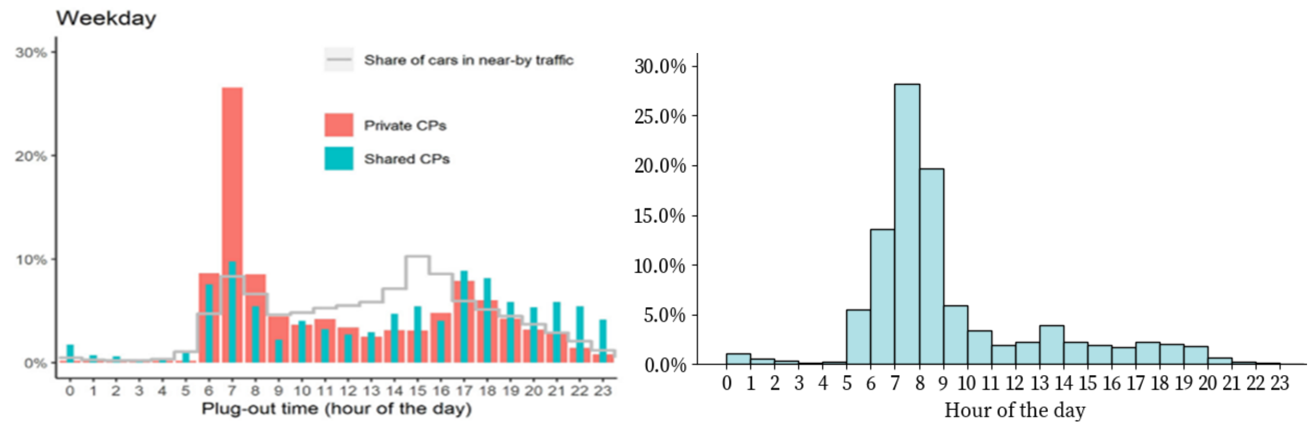


Figure 15: Distribution of plug-out times - Weekday for Norwegian data [11] (left) and simulation results (right).

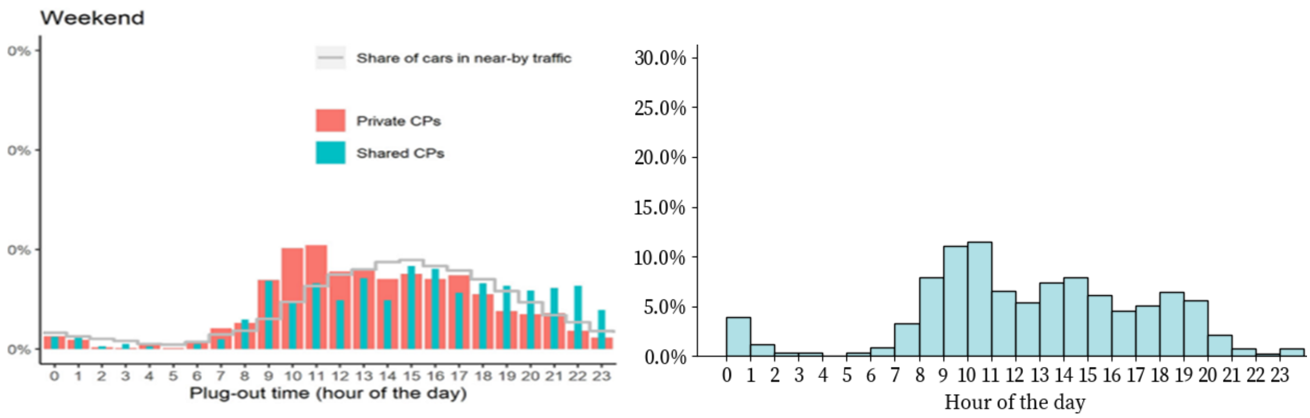


Figure 16: Distribution of plug-out times - Weekend for Norwegian data [11] (left) and simulation results (right).

4.2 Optimization framework

Short-term markets differ in terms of time scale and price variability. The different nature of each market implies different optimization strategies. The methodology for the Day Ahead optimization is based on *Mercier et al. (2023)*, studying DA arbitrage value for storage on DA markets across Europe [48]. The methodology for imbalance, intraday and coupled optimization strategy has been inspired by *Brijs et al. (2019)*, studying the value of storage by stacking revenue streams from the participation in all three short-term markets in a single operation strategy [49].

For all the further optimizations that have been implemented, the following assumptions are taken:

1. Perfect knowledge of the trips throughout the year:

For each trip of the year, departure and arrival time from/to home, and travelled distance are perfectly known.

2. Optimization from the retailer's point of view:

Only market prices are considered in the optimization. Consumer-side prices as well as grid fees are not considered. The considered gain therefore represents the gain that the retailer can make by optimizing its customers' charges on the markets and not the savings made by the user allowing his car to be used for optimization.

Nevertheless, if consumers increasingly become active players in the grid operations, by accepting to give up some level of comfort or take additional risks concerning their consumption, this cannot be achieved without redistributing them a part of the generated revenues [8]. The higher the consumers will receive from their explicit flexibility, the more they will be attracted by the idea of offering their flexibility.

3. The car is considered as always available for charging when at home:

EV users typically plug in their car every few days when they need to charge. The aim of this work is however to show the maximal gain that could be made in an optimization, and to examine whether there is an interest in improving current optimized charging, for example by incentivizing customers to plug in more often.

It is moreover reasonable to consider that people participating in an optimization, if they recuperate part of the revenues, would be keen to plug in their car more often. In a V2G trial involving 320 V2G units in the UK between January 2020 and December 2020, a survey of participants showed that 75% plugged in their car after every trip, and 18% after the last trip of the day [15]. Participants were paid a fixed rate for every kilowatt-hour that was exported.

4. Perfect foresight assumption:

It is considered that market prices are known in advance with full certainty. Concerning DA, real DA bids are made based on forecasted prices and are thus not perfectly optimal. However, as explained in [48], the reliability of this assumption has been tested by *Sioshansi et al. (2009)*. The authors optimized a 12-h duration storage in the PJM Interconnection (a regional transmission organization in the Eastern US serving 51 million people at the time of the paper), with optimization conducted two weeks at a time from 2002 to 2007 [50]. Authors compared optimization taking the perfect foresight assumption with a more realistic approach that does not include any foresight and optimized using the hourly prices of the past 2 weeks. This approach allowed to capture 85% to 90% of the value captured with the perfect foresight assumption.

Day-ahead prices are in fact to a large extent predictable with typical patterns such as day/night, weekday/weekends or seasonal price/load patterns. The perfect foresight assumption thus appears as an acceptable assumption in the case of day-ahead optimization.

Concerning imbalance and Intraday markets, the perfect foresight assumption is less evident. The real-time nature of those markets makes the price inherently uncertain. In reality, in those markets, action would be taken whenever the price is above or beneath a certain threshold, but results would then depend on these arbitrary thresholds (for example in imbalance: stop the charge when the imbalance price is above 200 €/MWh and start the charge when imbalance price is negative). I thus made the choice, as in *Brijs et al. (2019)* [49], to still rely on the perfect foresight assumption in my ID and imbalance optimizations but formulate the problem differently than in DA in order to limit its impact. This will be addressed in subsection 4.2.2.

5. Price taker assumption:

The price-taker assumption signifies considering the prices as given and not influenced by the fleet actions. This assumption is acceptable while the power and energy ratings of the EV fleet are relatively small compared to the size of the markets.

The modelled fleet of 2000 users consumes 5.26 GWh of energy over a year while in 2022, the total volume exchanged was 22 TWh in the DA market and 4.4 TWh in ID market [16].

Concerning power ratings, the fleet of 2000 users charging altogether at the same time would consume 16.4MW. As a comparison, looking at the system imbalance in Belgium in 2023, when the SI was negative, the median was 93.93 MW of missing energy and the SI reached more than 176.52 MW 25% of the time. On the other hand, when the SI was positive, the median was 75.48 MW and the SI reached more than 146.25 MW 25% of the time. The fleet is therefore small enough to be able to act in imbalance, but it should be noted, as already mentioned, that the imbalance market is not strictly speaking a market and that prices are set by the marginal cost of activating ancillary services. Acting on the imbalance is therefore in essence acting as a price-taker.

4.2.1 Day-ahead optimization

Because the auctions on the DA market are made daily for the next 24 hours, it seems natural to carry out the optimization with a horizon of 1 day. However, Figure 5 in subsection 3.2 has shown that DA prices are generally the lowest during weekends. Considering the relative predictability of DA prices and the perfect foresight assumption, one could allow energy shifts from day to day by choosing a larger optimization window. The time window of one week has been chosen to allow energy shifting to the weekends where the prices tend to be lower. The choice of one week allows that, whatever the starting weekday of the optimization window, the weekend days are considered in the optimal charging dispatch. As illustrated in Figure 17, a rolling approach is used where each day D, an optimization is performed on a weekly horizon, from D to D+6, to determine the transaction of the first day D. The State of Charge and energy charged at the first hour of D+1 are then used as initial values for the next optimization window.

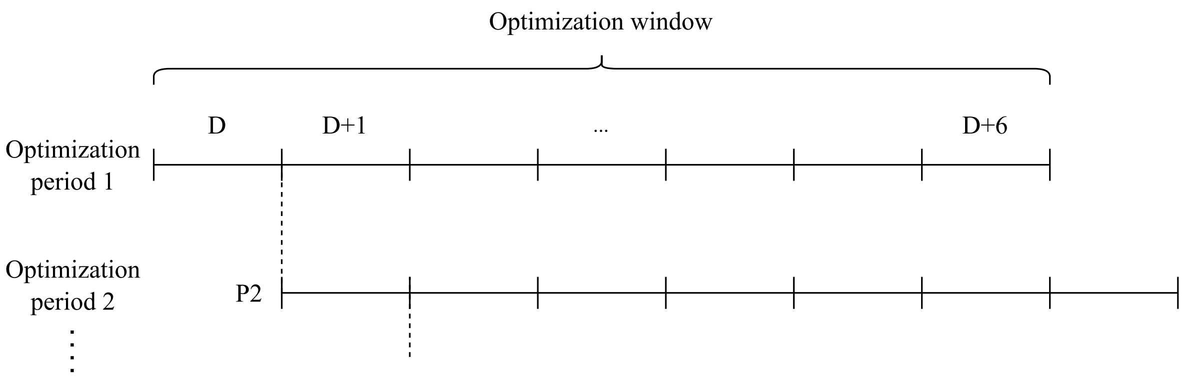


Figure 17: Illustration of the rolling approach optimization. Each optimization is computed on a weekly horizon to determine the transactions of the first day D. Initial state of charge and energy charged for the next optimization window are set equal to the one obtained at the start of D+1 of the previous run.

The problem is solved as a Linear Programming problem whose equations are displayed hereafter.

The objective function (1) aims to minimize the cost of recharge in the day-ahead market. Eq. (2) ensures the SoC remains in the acceptable range. This constraint was initially static, with min_{soc} set to 0 and max_{soc} set to 80% of the battery capacity, in accordance with literature [40]. However, keeping the minimum constraint to 0 led to unrealistic behavior where the user would charge only the very necessary energy for the trips, thus leaving home with a really low SoC that would not be acceptable for the user. A way to avoid customers leaving home with too low SoC is to impose to be charged at least 20% at the beginning of each trip. The constraint min_{soc} is then set to 20% at timestamps just before leaving home for a trip and is set to zero otherwise. On the other hand, it is advised to charge up to 80% most of the time, but the car sometimes needs to charge more if the length of the trip requires it. The constraint max_{soc} is then always set to 80%, except when it is required for the car to charge to 100% to be able to fulfill the next trip. Eq. (3) prevents charging more than what the charger's power rating permits, as well as when the car is not at home. Eq. (4) sets the initial value of SoC while Eq. (5) expresses the inter-temporal character of battery storage. For the DA optimization, the period T corresponds to one week divided in timestamps of 15 minutes.

Be T the set of timestamps i in the optimization window

Parameters
$\pi_{DA}[i]\ \forall i \in T$, the DA price in €/MWh
$min_{SOC}[i]\ \forall i \in T$, the minimal acceptable SoC
$max_{SOC}[i]\ \forall i \in T$, the maximal acceptable SoC
$cons[i]\ \forall i \in T$, the car consumption
E_{max}, the maximal charging energy

$$b[i] = \begin{cases} 1 & \text{if car at home} \\ 0 & \text{otherwise} \end{cases} \quad \forall i \in T$$

η, the charging efficiency

Variables
$E_{charged}[i]\ \forall i \in T$, the charged energy
$SOC[i]\ \forall i \in T$, the State of Charge

Objective function

$$min \sum_{i \in T} E_{charged}[i] \cdot \pi_{DA}[i] \tag{1}$$

Constraints

$$min_{SOC}[i] \leq SOC[i] \leq max_{SOC}[i] \qquad \forall i \in T \tag{2}$$
$$0 \leq E_{charged}[i] \leq E_{max} \cdot b[i] \qquad \forall i \in T \tag{3}$$
$$SOC[0] = SOC_{init} \tag{4}$$
$$SOC[i] = SOC[i-1] + E_{charged}[i] \cdot \eta - cons[i] \qquad \forall i \in T \text{ where } i \neq 0 \tag{5}$$

4.2.2 Intraday and imbalance optimizations

The imbalance and intraday markets have certain characteristics in common: their instantaneous nature makes it difficult to schedule the entire recharge exclusively in these markets, but the volatility of prices makes them good candidates for adapting an existing plan by taking advantage of large price variations. The approach detailed hereafter is thus common for the two optimizations, but these are two distinct optimizations which were tested separately.

Considering the different time scales of each market, it is considered, for the ID and imbalance optimizations, that the DA plan, whether it has been optimized or not, is known. As illustrated in Figure 18, optimization in those markets then constitutes an adaptation of the DA plan where one could stop the charge when it was planned to charge in DA (and then resell the electricity at the ID or imbalance price) and resume the charge later (and then buy back the electricity at the ID or imbalance price).

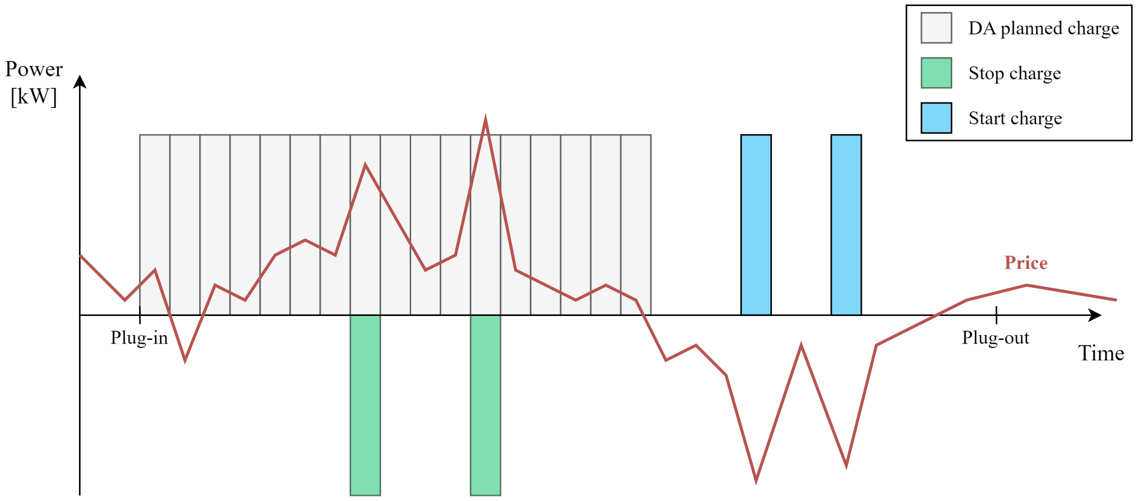


Figure 18: DA and imbalance optimization principle. The DA charging plan is known and in case of large ID/imbalance price while charging, the optimizer stops the charge to resell the electricity at the ID/imbalance price. It is imposed to get back to the DA planned SoC before the end of the session. The optimizer must then retrieve the charge within the same window and starts the charge at the cheapest ID/imbalance price.

As the perfect foresight assumption is less relevant for real-time markets as ID and imbalance, the optimization window has been reduced to one connection and it is imposed to get back to the DA planned SoC at the end of the optimization window. It allows limiting the actions that can be taken in those markets while making it more realistic as the DA-targeted SoC is the one allowing to fulfill the trips demand while keeping the SoC in an acceptable range for the user.

- **Intraday equations**

The optimizer still minimizes the charging cost, taking into account possible actions in Intraday (6). The energy charged in DA is known and thus considered as a parameter. Eq. (8) and (9) express that the optimizer can only stop the charge up to the amount it was planned to charge in DA and can only start charge to a quantity it was not already charging in DA. Eq (10) links the DA charging pattern and the charging pattern after ID optimization. Eq (7), (11), (12) and (13) constrain the SoC in the same way as in DA optimization, except that the SoC is also constrained to a final value in this case. The optimization window T is one connection session divided into timestamps of 15 minutes.

Be T the set of timestamps i in the optimization window

Parameters

$E_{DA}[i]$ $\forall i \in T$, the energy charged after the DA stage
$\pi_{DA}[i]$ $\forall i \in T$, the DA price in €/MWh
$\pi_{ID}[i]$ $\forall i \in T$, the ID price in €/MWh
$min_{SOC}[i]$ $\forall i \in T$, the minimal acceptable SoC
$max_{SOC}[i]$ $\forall i \in T$, the maximal acceptable SoC
E_{max}, the maximal charging energy
η, the charging efficiency
SOC_{init} and SOC_{final}, the initial and final SoC of the optimization window

Variables
$E_{start\_ID}[i]$ $\forall i \in T$, the charged energy in the ID stage
$E_{stop\_ID}[i]$ $\forall i \in T$, the stopped/resold energy in the ID stage
$E_{charged\_tot}[i]$ $\forall i \in T$, the energy charged after the ID stage
$SOC[i]$ $\forall i \in T$, the State of Charge

Objective function

$$min \sum_{i \in T} E_{DA}[i] \cdot \pi_{DA}[i] + (E_{start\_ID}[i] - E_{stop\_ID}[i]) \cdot \pi_{ID}[i] \tag{6}$$

Constraints

$$min_{SOC}[i] \leq SOC[i] \leq max_{SOC}[i] \qquad \forall i \in T \tag{7}$$
$$0 \leq E_{start\_ID}[i] \leq (E_{max} - E_{DA}[i]) \qquad \forall i \in T \tag{8}$$
$$0 \leq E_{stop\_ID}[i] \leq E_{DA}[i] \qquad \forall i \in T \tag{9}$$
$$E_{charged\_tot}[i] = E_{DA}[i] + E_{start\_ID}[i] - E_{stop\_ID}[i] \qquad \forall i \in T \tag{10}$$
$$SOC[0] = SOC_{init} \tag{11}$$
$$SOC[-1] = SOC_{final} \tag{12}$$
$$SOC[i] = SOC[i-1] + E_{charged\_tot}[i] \cdot \eta \qquad \forall i \in T \text{ where } i \neq 0 \tag{13}$$

- **Imbalance equations**

The imbalance optimization follows the same principle as the intraday one: the optimizer is rewarded with the imbalance price when stopping a charge that was planned in DA and must pay the imbalance price to resume this charge within the optimization window. To stick with the reality and the system needs, a binary constraint is added in Eq. (16) and (17) to allow the charge to stop only when the system imbalance is negative (shortage of energy), and to start a charge only when the system imbalance is positive (surplus of energy).

Be T the set of timestamps i in the optimization window

Parameters
$E_{DA}[i]$ $\forall i \in T$, the energy charged after the DA stage
$\pi_{DA}[i]$ $\forall i \in T$, the DA price in €/MWh
$\pi_{imb}[i]$ $\forall i \in T$, the imbalance price in €/MWh
$min_{SOC}[i]$ $\forall i \in T$, the minimal acceptable SoC
$max_{SOC}[i]$ $\forall i \in T$, the maximal acceptable SoC
E_{max}, the maximal charging energy
η, the charging efficiency
SOC_{init} and SOC_{final}, the initial and final SoC of the optimization window

$$b_{SI}[i] = \begin{cases} 1 & \text{if SI} > 0 \\ 0 & \text{if SI} <= 0 \end{cases} \quad \forall i \in T$$

η, the charging efficiency

Variables

$E_{start\_imb}[i]$ $\forall i \in T$, the charged energy in the imbalance stage

$E_{stop\_imb}[i]$ $\forall i \in T$, the stopped/reselled energy in the imbalance stage

$E_{charged\_tot}[i]$ $\forall i \in T$, the energy charged after the imbalance stage

$SOC[i]$ $\forall i \in T$, the State of Charge

Objective function

$$min \sum_{i \in T} E_{DA}[i] \cdot \pi_{DA}[i] + (E_{start\_imb}[i] - E_{stop\_imb}[i]) \cdot \pi_{imb}[i] \tag{14}$$

Constraints

$$min_{SOC}[i] \leq SOC[i] \leq max_{SOC}[i] \qquad \forall i \in T \tag{15}$$

$$0 \leq E_{start\_imb}[i] \leq (E_{max} - E_{DA}[i]) \cdot b_{SI} \qquad \forall i \in T \tag{16}$$

$$0 \leq E_{stop\_imb}[i] \leq E_{DA}[i] \cdot (1 - b_{SI}) \qquad \forall i \in T \tag{17}$$

$$E_{charged\_tot}[i] = E_{DA}[i] + E_{start\_imb}[i] - E_{stop\_imb}[i] \qquad \forall i \in T \tag{18}$$

$$SOC[0] = SOC_{init} \tag{19}$$

$$SOC[-1] = SOC_{final} \tag{20}$$

$$SOC[i] = SOC[i-1] + E_{charged\_tot}[i] \cdot \eta \qquad \forall i \in T \text{ where } i \neq 0 \tag{21}$$

4.2.3 Coupled optimization

Brijs et al. (2019) proposed 2 optimization strategies coupling DA, ID and imbalance markets: one sequential and one coordinated [49]. In the sequential strategy, each market is optimized separately in chronological order: the price of charging is first minimized in DA, and the optimized DA charging pattern is used as an input for the ID stage. The result of the ID optimization is itself used as an input charging pattern for the imbalance optimization. In the coordinated strategy, at each decision stage, all market prices are considered simultaneously, i.e. the imbalance and ID prices are known and taken into account in the DA optimizer decisions. The authors concluded that the coordinated approach was the most profitable strategy, with the imbalance market driving the most value. It is however specified that the coordinated approach is yet more risky and less realistic, as the operator can anticipate large (favorable) imbalance by a priori creating a position in the other direction in DA.

The methodology proposed in this work is inspired by the paper's methodology, but adapted in the aim of correcting certain shortcomings.

Firstly, the paper uses a 2-day window optimization for each market. However, the different market characteristics should imply different optimization periods. Moreover, the coordinated strategy (imbalance and ID prices known at the DA stage) appears unrealistic, but the sequential strategy misses part of the point, as the instantaneous nature of ID and imbalance markets could confer interest in a coordinated strategy of these two markets.

Taking into account the abovementioned considerations, the strategy proposed in this work combines two optimization windows: a first optimization is held in DA as explained in subsection 4.2.1, and the optimal charging pattern is used as an input for a coordinated ID and imbalance optimization. I first implemented an optimization allowing to stop and start charges both in the ID and the imbalance market. However, when relying on the perfect forecast assumption, this coupled optimization does not provide added value compared with an optimization based solely on DA and imbalance: the optimizer rarely acted in intraday as imbalance prices are in most cases more attractive than ID prices.

A strategy combining the 3 markets therefore does not provide significant added value in revenue terms, compared with a strategy combining only DA and imbalance, but it could present other benefits. Indeed, when an action is decided in the imbalance market, for instance stopping a charge, the optimizer must retrieve the charge later in the same optimization window, meaning that we know up to some hours in advance that we will have to buy back electricity. Instead of waiting for an opportunity in imbalance, one could buy back electricity in ID, securing the charge up to some hours in advance at a known price. It was eventually concluded that the added value of such optimization could lie in risk management rather than financial value. It has thus been decided to implement a coupled strategy to authorize stopping charges in imbalance and then buy back the charges in the ID market.

Finally, two coupled strategies have been implemented:

- A sequential optimization coupling DA and imbalance: a first optimization is performed in DA as explained in subsection 4.2.1. The DA-optimized charging pattern is then used as an input for a second optimization in imbalance as explained in subsection 4.2.2.
- An optimization coupling the 3 markets: a first optimization is performed in DA followed by a coordinated optimization where the optimizer is authorized to stop charges only in imbalance and to restart charges only in intraday. The added value of this optimization lies more in risk management than in financial value. Equations are displayed hereafter.

Be T the set of timestamps i in the optimization window

Parameters

$E_{DA}[i]$ $\forall i \in T$, the energy charged after the DA stage
$\pi_{DA}[i]$ $\forall i \in T$, the DA price in €/MWh
$\pi_{ID}[i]$ $\forall i \in T$, the imbalance price in €/MWh
$\pi_{imb}[i]$ $\forall i \in T$, the imbalance price in €/MWh
$min_{SOC}[i]$ $\forall i \in T$, the minimal acceptable SoC
$max_{SOC}[i]$ $\forall i \in T$, the maximal acceptable SoC
E_{max}, the maximal charging energy
η, the charging efficiency
SOC_{init} and SOC_{final}, the initial and final SoC of the optimization window

$$b_{SI}[i] = \begin{cases} 1 & \text{if SI} > 0 \\ 0 & \text{if SI} <= 0 \end{cases} \quad \forall i \in T$$

η, the charging efficiency

Variables

$E_{stop\_imb}[i]$ $\forall i \in T$, the stopped/resellled energy in the imbalance market
$E_{start\_ID}[i]$ $\forall i \in T$, the charged energy in the ID market
$E_{charged\_tot}[i]$ $\forall i \in T$, the energy charged after the ID-imbalance optimization
$SOC[i]$ $\forall i \in T$, the State of Charge

Objective function

$$min \sum_{i \in T} E_{DA}[i] \cdot \pi_{DA}[i] - E_{stop\_imb}[i] \cdot \pi_{imb}[i] + E_{start\_ID}[i] \cdot \pi_{ID}[i] \tag{22}$$

Constraints

$$min_{SOC}[i] \leq SOC[i] \leq max_{SOC}[i] \qquad \forall i \in T \tag{23}$$
$$0 \leq E_{start\_ID}[i] \leq (E_{max} - E_{DA}[i]) \qquad \forall i \in T \tag{24}$$
$$0 \leq E_{stop\_imb}[i] \leq E_{DA}[i] \cdot (1 - b_{SI}) \qquad \forall i \in T \tag{25}$$
$$E_{charged\_tot}[i] = E_{DA}[i] + E_{start\_ID}[i] - E_{stop\_imb}[i] \qquad \forall i \in T \tag{26}$$
$$SOC[0] = SOC_{init} \tag{27}$$
$$SOC[-1] = SOC_{final} \tag{28}$$
$$SOC[i] = SOC[i-1] + E_{charged\_tot}[i] \cdot \eta \qquad \forall i \in T \text{ where } i \neq 0 \tag{29}$$

4.3 Revenue Calculations

As the timescale and way of optimizing are different for DA compared to ID and imbalance, the ways of computing the optimization benefits also differ.

In the case of the DA optimization, optimization consists of completely remodelling the charging pattern to charge at the cheapest hours. The benefit of optimization therefore lies in cost savings compared with a reference case where the charge would not be optimized. The selected reference case is the uncontrolled natural charging case, i.e. charging starts directly when the car is plugged in and continues until the maximum SoC is reached, with the electricity bought in DA.

$$\textit{Revenue} = \textit{DA cost of uncontrolled charging} - \textit{cost of DA-optimized charging}$$

Concerning ID and imbalance, optimization starts from an existing DA planned charging pattern and deviates from this plan within a charging session to stop the charge (resell electricity) and restart the charge (rebuy electricity) whenever there are interesting opportunities in these markets. As it is imposed to go back to the DA planned SoC at the end of the charging session, any charge that has been stopped must be recovered within the same connection period, and value generation relies on stopping the charge at a high ID/imbalance price and restarting the charge at a low or negative ID/imbalance price.

$$\textit{Revenue} = \textit{Resale gain when stopping charge} - \textit{buy-back cost when restarting the charge}$$

4.4 Input data

The optimizations take as an input the simulated EV fleet with the associated uncontrolled charge patterns as well as price series.

First, a virtual EV fleet consisting of 2000 users is generated as explained in subsection 4.1, with a battery capacity, vehicle electrical consumption and a charger power rating probabilistically attributed to each user. Natural charges, as well as the following charging optimizations are conducted over one year on a quarter-hourly resolution. This resolution is used in most short-term markets and allows a trade-off between computation time and sufficient precision.

Historical DA and imbalance prices were obtained on Elia's open data portal [51]. ID indices have been obtained in the Engie internal database. The year 2023 has been selected as it is the most recent complete year, marking a return to stability after years of high price volatility due to COVID-19 and the war in Ukraine.

4.5 Fleet analysis

One of the aims of this work is to understand what consumer characteristics could influence their flexibility potential. This section describes the approach used to study the impact of input characteristics on the outputs of the optimizations: the revenue and the amount of energy moved by the user.

It is worth first defining some input metrics that are likely to have an impact on the chosen outputs. The following metrics have been defined or computed for each user:

- The number of kilometers driven over the year.
- The battery capacity.
- The nominal charging power.
- The number of teleworking days per week.
- The average amount of kilowatt-hours charged per session, as well as the number of charges per week.
- The percentage of charges starting on a weekday, Saturday or Sunday.
- The percentage of charge starting at night (0 am to 6 am), in the morning (6 am to noon), in the early afternoon (noon to 3 pm), in the late afternoon (3 pm to 6 pm) and in the evening (6 pm to midnight).
- The SoC threshold for starting a charge.

The conventional correlation matrix can be used to measure the correlation between the inputs and the outputs metrics. In addition, I used a random forest regressor to analyze the importance of input parameters on the output. The *RandomForestRegressor* module from *scikit-learn* allows for the creation of a regression model that aims to predict the decided output variable based on input metrics [52]. The built-in *feature_importances_* attribute then identifies the importance of each input feature to the model's predictions. The use of the Random Forrest Regressor allows capturing more complex relationships between features and targets, as well as interactions or combined effects that would not appear in a simple linear correlation. Further explanations on the functioning of the regressor can be found in Appendix B.

5 Results

Optimizations have been implemented in python, using the pyomo optimization package and applied to a fleet of 2000 generated users charging on average 2600 kWh/year. Global results will first be analyzed in terms of revenue, before delving into the details of each optimization and the inputs (riding behavior or EV characteristics) influencing the users' revenue.

5.1 Global results

Table 8 shows the average financial gain of optimizing the charge in function of the optimization strategy. The first row shows the absolute gain per user and per year (computed as explained in subsection 4.3) while the second row shows the normalized revenue, i.e. the relative gain compared to the initial cost of charge.

	DA	ID	Imb	DA + imb	DA + imb + ID
Revenue [€/user.year]	200.31	169.28	417.34	498.92	343.53
Normalized revenue [%]	72.51	59.76	148.2	178.63	123.32

Table 8: Optimizations revenue. Normalized revenue is the relative gain in percentage of the initial cost of charge. Optimization coupling day-ahead and imbalance is the most profitable.

It can be observed that the ID optimization holds less value than the DA optimization, which might appear surprising as the ID prices are similar to DA price but with more volatility and thus carry more opportunity to buy/sell electricity at low/high price. The temporality and the strategies employed in the optimization are however very different: the DA optimization allows shifting energy on a weekly basis while the ID optimization is restricted to one connection time and is imposed to come back at the DA plan at the end of the optimization, limiting the possible actions. The ID optimization is thus more restricted in the energy shifting opportunity: in DA optimization, 93.38% of the energy has been displaced compared to the natural charging pattern, while the ID optimization allowed to shift 79.63% of the total energy charged.

Among the mono-market strategies, the imbalance optimization is the most profitable, more than doubling the revenue compared to the DA optimization. Although using the same optimization approach as intraday, which did not turn out to be very interesting, the imbalance prices show much greater amplitudes of variation (see Figure 19), resulting in greater value generation.

The optimization coupling DA and imbalance carry even more value, but it is interesting to note that when splitting the revenue of this coupled optimization, the DA stage generated €200.31 by user and by year and the following imbalance optimization generated €298.61. The revenue generated by the imbalance optimization is thus reduced by 28.52% if a DA optimization is first performed. It can be explained because in the natural case, charges occur at peak hours when demand is already high and where there is a high potential of stopping charge. When the charge is already DA optimized, this possibility does not appear anymore. Concerning the optimization coupling DA, ID and imbalance, it appears to be less profitable than the coupled DA-imbalance

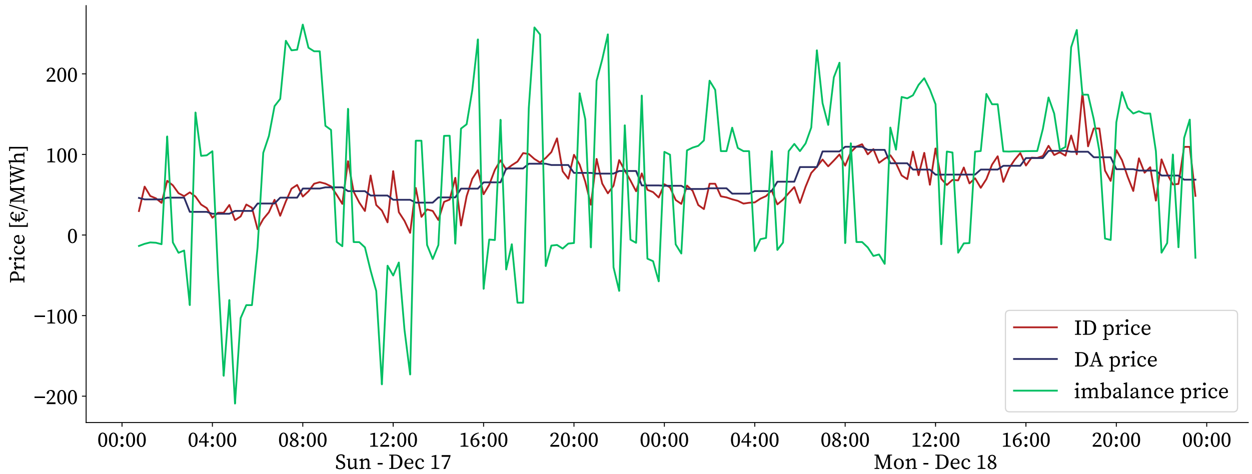


Figure 19: Comparison of day-ahead, intraday and imbalance prices on 17 and 18 December 2023. Imbalance prices show much greater amplitude variations than ID prices, making imbalance optimization the most profitable.

optimization. As explained in subsubsection 4.2.3, this strategy allows only to stop charges in imbalance and to buy back the charges in intraday, and its value lies more in risk management than in increased profitability.

5.2 In-depth analysis

This section aims to study more in detail optimization results and whether it is possible to identify user characteristics, regarding either their behavior or the characteristics of the car and charger, which influence the potential for flexibility.

5.2.1 Day-ahead optimization

Figure 5 in subsection 3.2 showed that DA prices were on average lower at night and during weekends. Figure 20 shows that the DA optimization effectively shifts the charges in those periods.

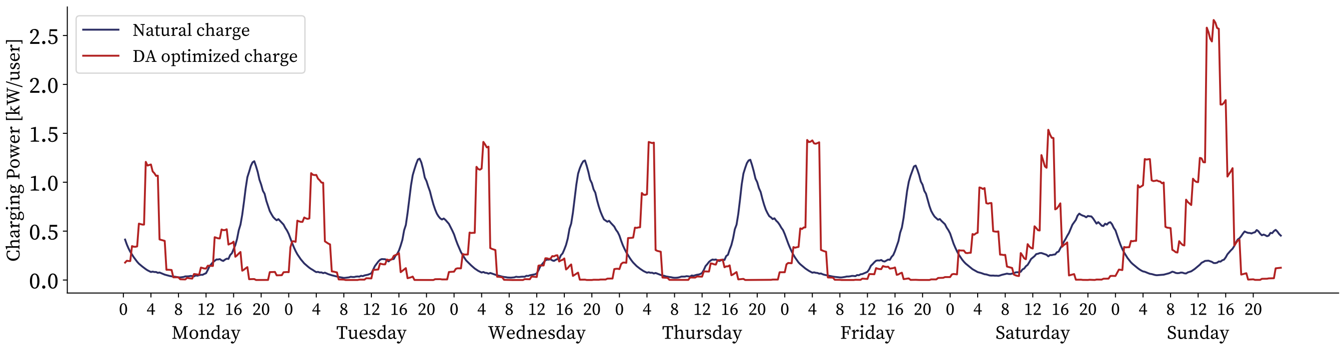


Figure 20: Weekly average energy charged for the natural and the DA optimized cases. The DA optimization allows shifting the charging peaks later in the night as well as in the weekend.

Looking at identifying tendencies in the revenue generation, a first evident answer is that the revenue generated by the DA optimization - as well as all other optimization strategies - is directly correlated with the number of kilometers travelled per year, as it can be observed in Figure 21.

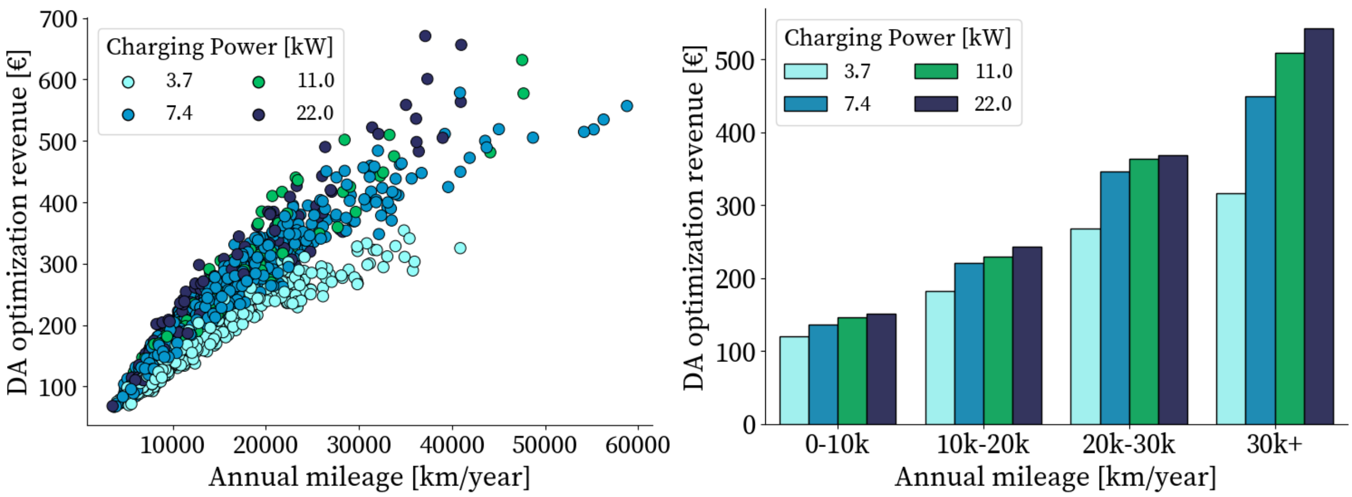


Figure 21: DA optimization revenue in function of the annual mileage and the charging power rating. The revenue is directly correlated with the number of kilometers travelled by year. For equivalent mileage, greater charging power rating generates more value.

The more kilometers you drive, the more energy you need to charge, so the more you can displace by optimizing the charge. Users travelling less than 10,000 kilometers generate an average of €134.31, those between 10 and 20,000km €212.02, those between 20 and 30,000 €325.82 and those over 30,000 €445.10. The analysis also identifies nominal charging power as a parameter influencing income: for equivalent mileage, greater charging power generates more value. This is all the more true for intensive users, where we see the biggest difference in revenue between small and large power ratings: the more users drive, the more they have to charge, and a low-power charger requires charging for a longer time, reducing the amount of energy that can be shifted around.

The battery capacity is another factor influencing the revenue, as depicted in Figure 22, with a greater battery capacity allowing to charge more energy during the cheapest windows.

Large consumers hold the biggest revenue, but also the biggest initial cost. Only looking at absolute revenue could then lead to only incomplete conclusions. Looking at normalized revenues, expressed in percentage of the initial charging cost, and at the percentage of energy moved compared to the initial charging pattern, we can see that big consumers generate this time less value compared to their initial charging cost (Figures 23 and 24). As before, the rated charging power influences the possibilities for flexibility, with greater power allowing charging only at times when energy is affordable and therefore generating more value.

Concerning DA optimization, it can be concluded that the total energy demand, linked to the number of kilometers travelled per year is the most important factor influencing the revenue. For equivalent mileage, a greater charging power rating generates more value, with a low power rating limiting the possibility of energy shifting, especially for large consumers. A greater battery capacity also enables to generate more revenue as it allows more energy to be charged in the cheapest windows.

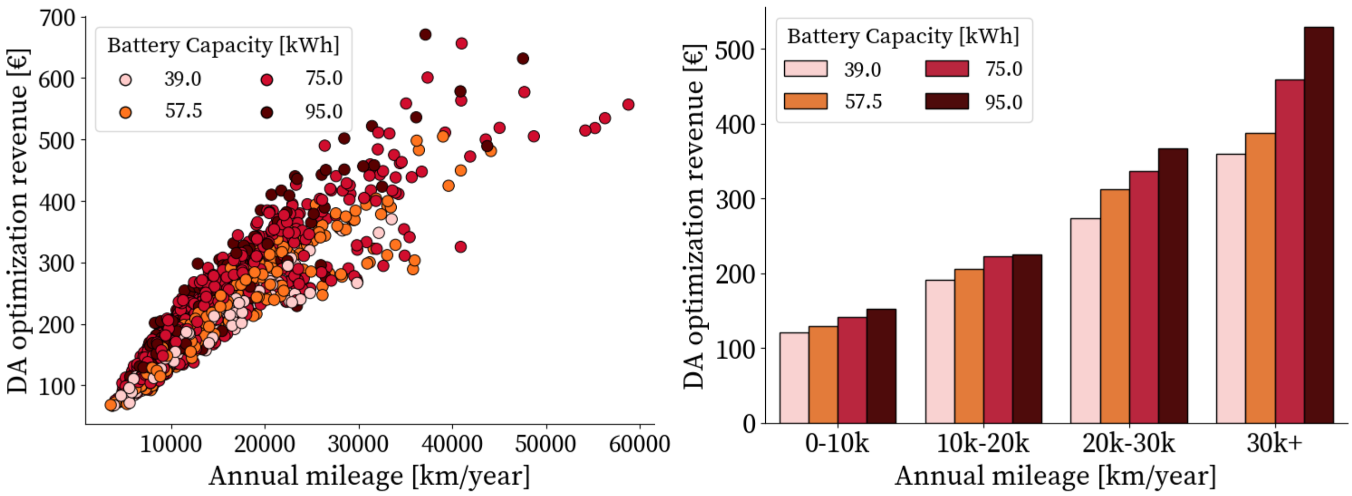


Figure 22: DA optimization revenue in function of the annual mileage and the battery capacity. The revenue is directly correlated with the number of kilometers travelled by year. Greater battery capacity gives greater revenue.

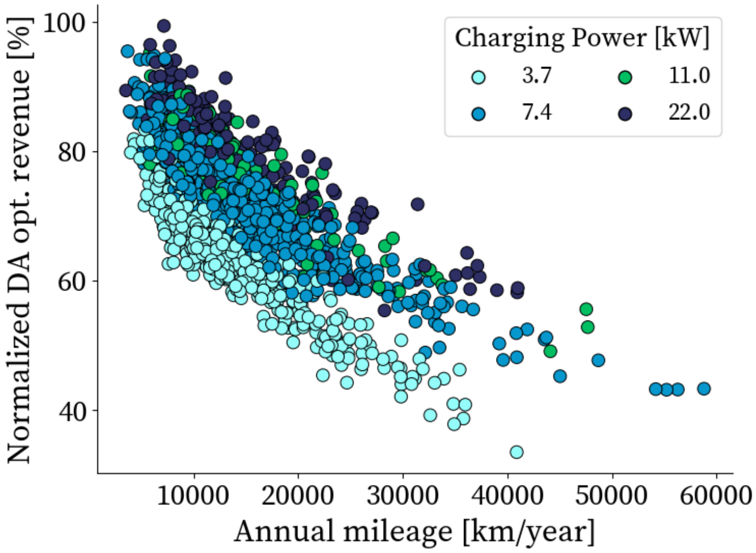


Figure 23: Normalized revenue (expressed in percentage of the initial charging cost) decreases as the user's annual mileage increases. For equivalent mileage, a greater power increases the normalized revenue.

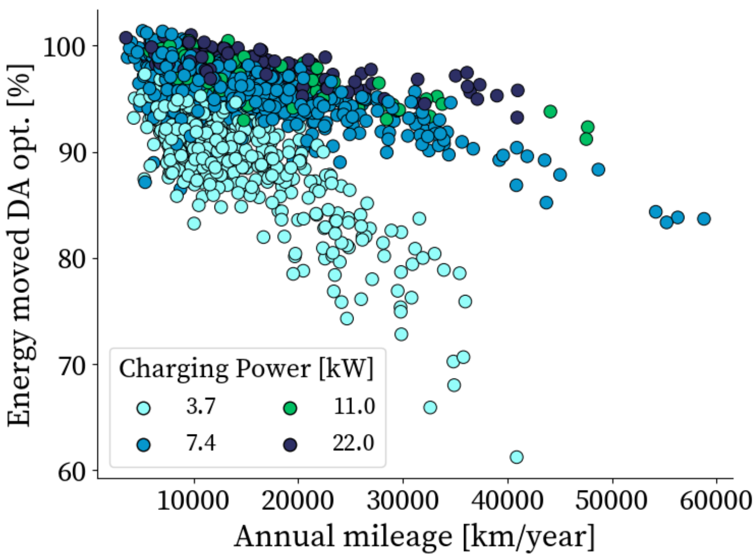


Figure 24: Energy shifting potential decreases as the user's mileage increases. At equivalent mileage, higher charging power rating allows to move more energy.

5.2.2 Imbalance optimization

Considering imbalance optimization, the number of kilometers travelled by year is still the parameter influencing the most absolute revenue: the more we drive, the more we can generate revenues (Figure 25). Once again, greater power means greater flexibility, but no tendency is observed depending on battery capacity (Figure 26). In the DA optimization, a greater battery capacity allows to shift more energy during the cheapest hours (for instance by making a full charge on Sunday for the whole week). As in imbalance, the optimization is performed within a session (energy can only be shifted within the same connection window), battery capacity is no longer impactful for the revenue generation.

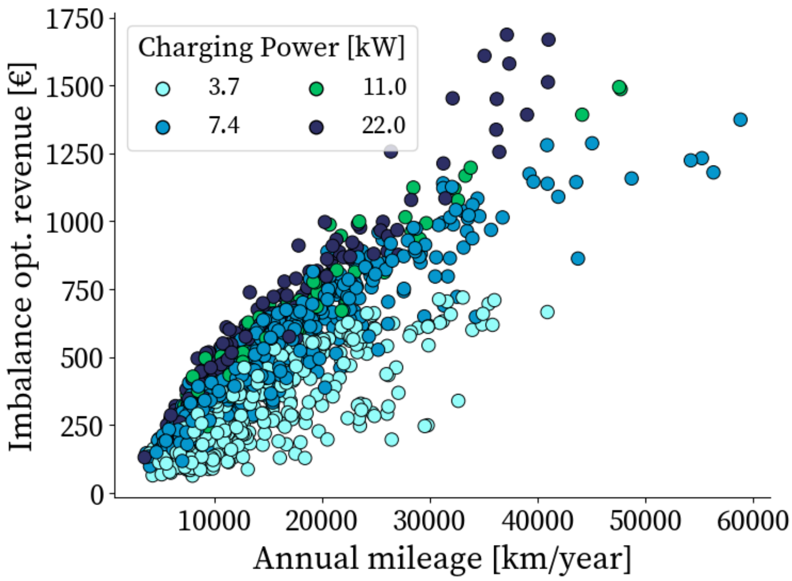


Figure 25: Imbalance optimization revenue in function of the annual mileage. The revenue is directly correlated with the number of kilometers travelled by year. For equivalent mileage, greater charging power rating generates more value.

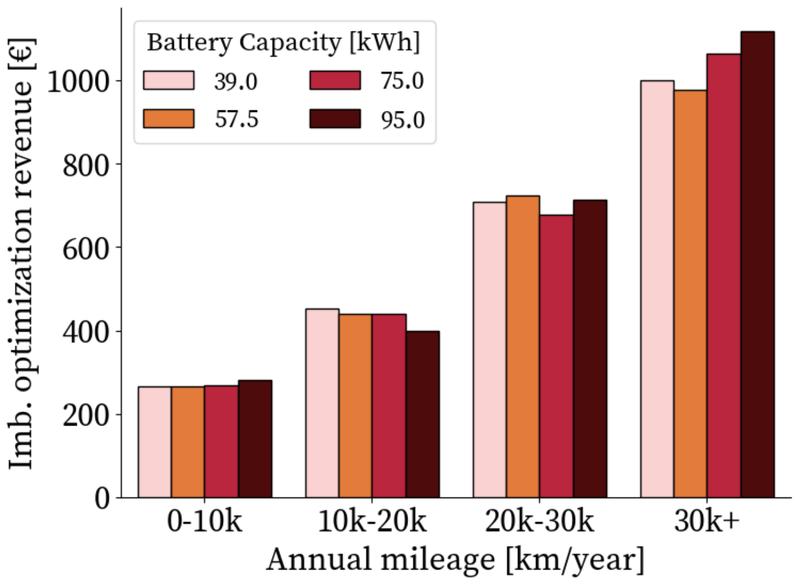


Figure 26: Imbalance optimization revenue in function of the annual mileage and the battery capacity. No tendency is observed depending on the battery capacity.

Looking at normalized revenue and the percentage of energy shifted, the features importance analysis showed the importance of the user behavior on the flexibility potential (see Figures 50 and 51 in Appendix B). As a reminder, in the simulated fleet, each user is attributed a threshold above which it will not start the charge. The average quantity of energy charged per session, used in Figures 27 and 28 to compare user's normalized revenues and percentage of energy moved by the optimization, is directly correlated with the user's SoC threshold: for the same annual quantity of energy charged and the same battery capacity, a user with a threshold of 40% will charge less often but more energy per charge than a user with a threshold of 70%. Figures 27 and 28 show that users charging on average more energy per session can release less flexibility.

The average energy charged per session is important in this case because as we impose that the optimization window is one session and to get back to the DA planned SoC at the end of the optimization, we act on imbalance only if we were charging energy in DA. If it was planned in DA to charge a lot of energy, the time needed for charging is greater in proportion compared to the connection time and leaves thus fewer available slots to shift the energy. For instance, if a user plugs in at night to charge 40 kWh with a 3.7 kW charger, it will take almost 11 hours to fully charge, which leaves very little room to shift the charge. The users corresponding to this scenario in Figure 28 are indeed those shifting the least energy, in proportion to the total energy charged.

In conclusion, regarding imbalance optimization, kilometers travelled, as well as nominal charging power, are still the key elements determining the revenue generated. In addition, as we optimize within a session, the user's behavior is this time also important: a user who charges often but little energy unlocks more flexibility than a user who charges rarely but therefore with larger quantities of energy per charge.

The intraday optimization results follow the same trend as the imbalance results. They therefore lead to the same conclusions and are not further discussed, but can be consulted in Appendix C.

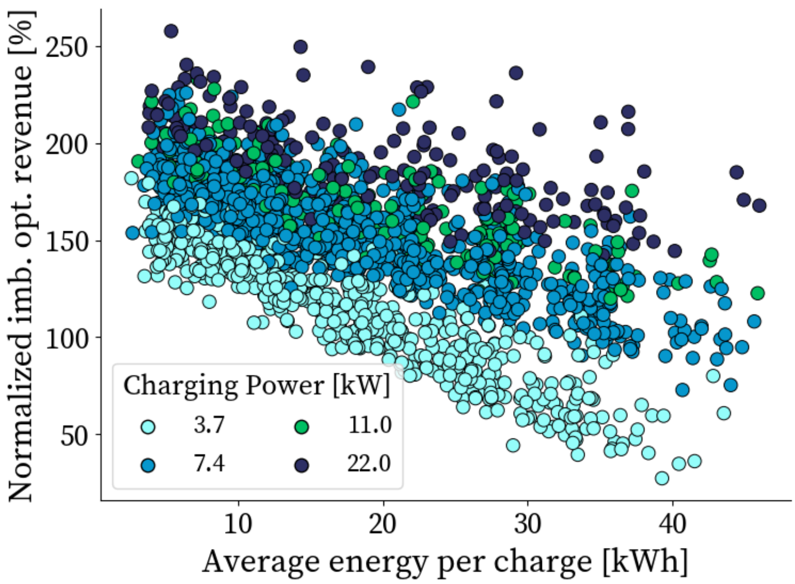


Figure 27: Normalized revenue (expressed in percentage of the initial charging cost) decreases as the user charges on average more energy per session. A greater power increases the normalized revenue.

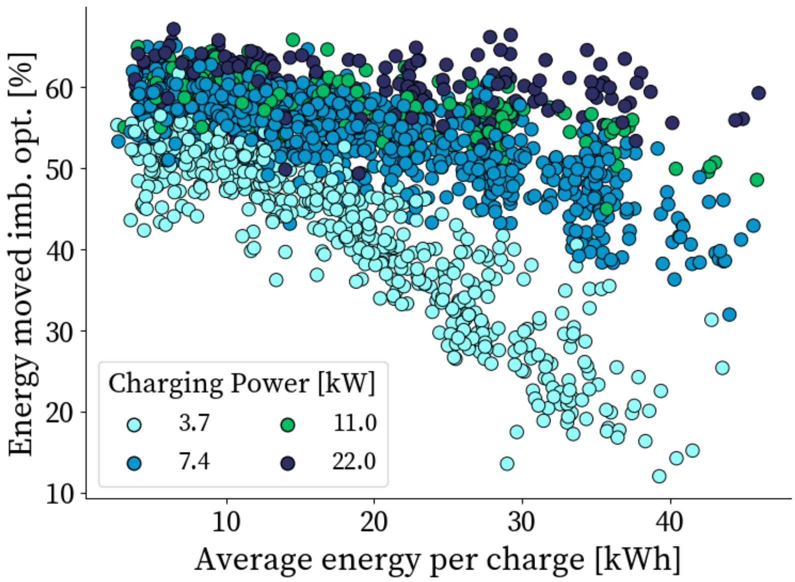


Figure 28: Energy shifting potential decreases as the user charges on average more energy per session. Higher charging power rating allows to move more energy.

5.2.3 Coupled optimizations

The strategy coupling DA and imbalance, as well as the strategy coupling the three markets, presents similar conclusions to those already presented. Figures illustrating the results can be consulted in Appendix C.

The number of kilometers travelled per year is still the most impacting parameter influencing the revenue. In addition, for equivalent mileage, greater charging power generates more value. To a lesser extent, battery capacity also has an influence, with higher capacity allowing longer charges in low-cost windows.

5.3 Discussion on the impact of some assumptions

When analyzing these results, it is important to bear in mind the assumptions that have been formulated (in subsection 4.2) and how these might impact the realism of the results. Two assumptions in particular are discussed hereafter: the 100% availability of cars when at home and the perfect foresight assumption for the imbalance market.

5.3.1 Users availability

Firstly, it has been assumed that the vehicles were always available for charging when they are at home. In reality, users currently plug their cars only when they really want to charge. In Belgian recharging data, recently gathered from Jedlix charge optimization for Engie customers[5], cars were connected 22.7% of the time spent at home. Assuming 100% availability is thus not realistic and may lead to over-optimistic revenue as more availability offers more room for energy shifting.

To compare the results with something more representative of what is currently in place, the optimizations have been re-simulated with adaptations intended to better represent current user behavior in terms of the availability of the car for charging:

1. The reference case is no longer the natural charge which would start as soon as the user plugs in, but a charge taking into account off-peak tariffs. Electricity suppliers offer special tariffs for EVs charging (Engie, for example, offers the Drive contract with advantageous tariffs at night and at weekends). It is not unreasonable to think that users will first look to reduce their electricity bill before leaving their car available for optimization. If we consider the "*off-peak charging*" case as the reference case, the car no longer charges during peak hours, so the potential for savings should be reduced.
2. It is no longer assumed that the car is available 100% of the time at home, rather that it is connected only when the user really intends to charge, i.e. a session is engaged in the optimizer only when a session was also engaged in the uncontrolled case. This should particularly impact the DA optimization as the optimizer was previously allowed to shift energy whenever the car was at home in a weekly horizon.
3. The simulated fleet is made up of "*top-up chargers*", which plug the car in regardless of the SoC when returning from a journey, and "*soc chargers*", which only plug the car in when the SoC falls below a certain threshold. Examination of the Jedlix data for Engie showed that in the real fleet analyzed, there were rarely, if at all, charges starting with a high initial SoC, showing that the "*top-up chargers*" may not be representative of reality. The "*top-up*" chargers were therefore removed from the analysis, leaving only the "*soc chargers*" (1,385 of the 2,000 users).

Assuming that the car is only available for charging during off-peak hours, only when the user really intends to charge, and keeping only the "*soc chargers*" with a behavior closer to that observed in the Jedlix data, the availability of the cars in the simulated fleet when the user is at home falls from 100% of the time to an average of 26.06%. This brings us closer to the availability statistics for the real fleet. New average costs taking into account the reduced

[5] We now have access, after filtering, to 1095 home charging users with data from June 2023 to February 2024.

availability are indicated in Table 9 and Figure 29 shows the comparison with the initial optimization considering 100% availability.

The DA optimization is the most affected by these input changes, with revenues reduced by around half (€105.43 per user compared to €200.31 for the first optimization). In the first optimizations, the DA optimization allowed energy to be shifted freely to the cheapest hours within a 7-day timeframe. We are now constrained by the availability of the car, reducing the possibilities for energy shifting.

	DA	ID	Imb	DA+ imb	DA + imb + ID
Revenue [€/user.year]	105.43	108.96	283.16	312.81	212.26
Normalized revenue [%]	42.71	44.03	114.95	125.91	86.17

Table 9: Optimization results with reduced availability and filtered fleet.

The imbalance and ID optimizations are less affected, as they were taking place within a connection session anyway, and the reduction observed is more due to the introduction of the off-peak tariff reducing the optimization window to off-peak hours (ID optimization revenues are reduced by 35.63%, imbalance optimization revenues by 32.15%, coupled DA and imbalance revenues by 37.30% and the coupled DA, ID and imbalance optimization revenues by 38.21%).

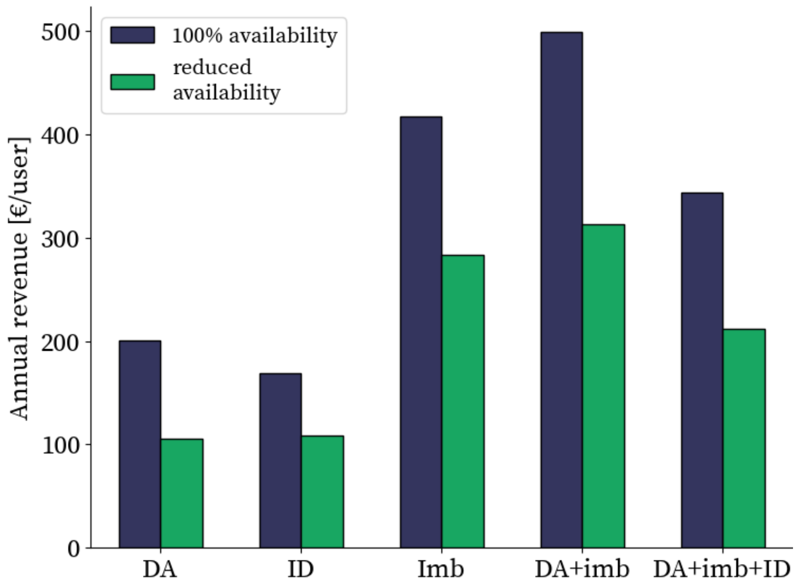


Figure 29: Comparison of the average annual revenue in the standard case (100% availability) and the case with reduced availability and filtered fleet. DA optimization is the most impacted by the reduced availability, with revenues divided by around a half. Other optimizations see a reduction in revenue of around -35%.

As before, it is the annual travelled distance and the charging power that influence the most the revenue (Figure 30).

Moreover, user behavior this time takes on even more importance on the absolute revenue, with users connected the most that generate more revenue, as depicted in Figure 31 for the DA optimization. In addition, with 100% availability, a greater battery capacity allowed to generate more revenue in the DA optimization. This relation do not appear anymore with a reduced availability (Figure 32).

Given the large reduction in revenue when reducing the users availability, and the fact that when we do so, users with greater availability generate more revenue, it can be concluded that revenue-wise, it is worth incentivizing users to connect more often.

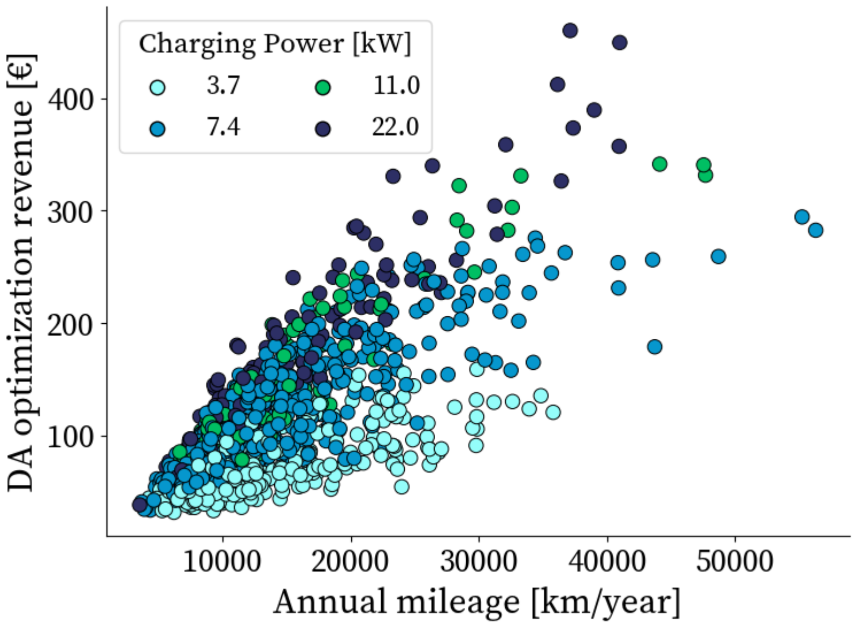


Figure 30: DA optimization revenue in function of the annual mileage and the charging power rating, with reduced availability and filtered fleet. The revenue is directly correlated with the number of kilometers travelled by year. For equivalent mileage, greater charging power rating generates more value.

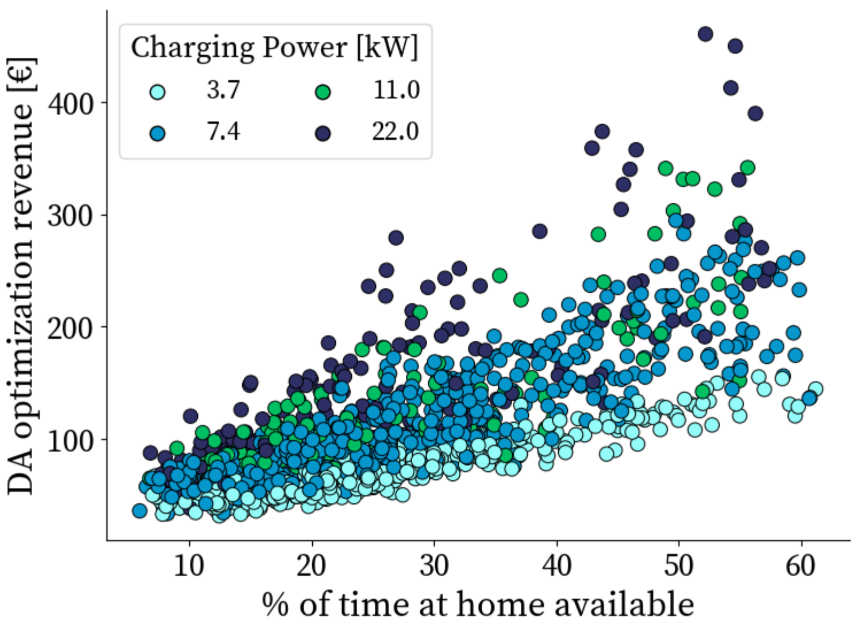


Figure 31: DA optimization revenue in function of the user's availability at home and the charging power rating, with filtered fleet. Users connected the most generate more revenue.

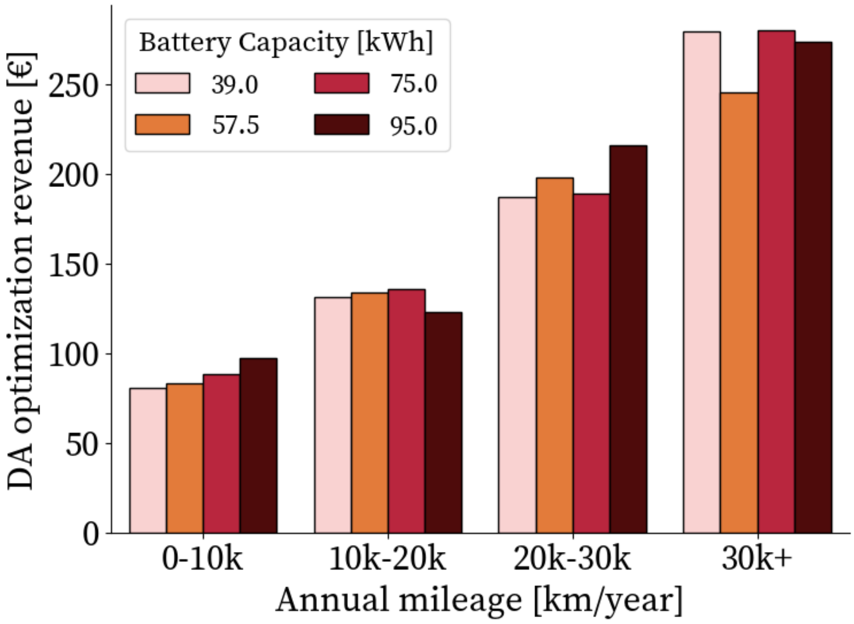


Figure 32: With 100% availability, a greater battery capacity allowed to generate more revenue. This relation do not appear anymore with a reduced availability.

5.3.2 Perfect price foresight assumption

While the perfect foresight assumption is quite realistic for the DA optimization, it is less the case for the ID and imbalance markets that are inherently unpredictable and the results for these optimizations are therefore over-optimistic. It nevertheless allows to obtain an upper bound for the potential value generation, to compare the different optimizations on the same basis, and to determine whether a coupled strategy can generate additional value.

Obtaining more realistic results would require the relaxation of the perfect foresight assumption. However, formulating an optimization without perfect foresight assumption appears somewhat complex. In reality, players acting on the imbalance market would not wait until the best moment to act, as this moment is unknown, but would act whenever the imbalance price is above or beneath a certain threshold. A realistic operation strategy would then be sequential but is rather complex to model taking into account that the quantity of energy to charge is finite, and every action taken in one direction must be later retrieved in the other direction. This would require a strategy which, at each time step, makes a decision taking into account the current state of the car (charging or not), the current system imbalance and imbalance price, the previous actions on the imbalance market and the targeted SoC. I lacked time to implement such a strategy which might be a good suggestion for future work.

However, to show a more realistic order of magnitude regarding imbalance gains without completely changing the optimization strategy, I reran the imbalance optimizations, adding thresholds to act depending on the imbalance price: an upper threshold below which the charge will not be stopped, and a lower threshold above which the charge will not be retrieved. Those thresholds represent the willingness of actors to act only for relevant price signals, and their value choice is arbitrary and based on the intuition of what is an imbalance price that would encourage players to act. I choose an upper threshold of 200€/MWh (the charge is stopped only for an imbalance price above 200€/MWh) and a lower threshold of 0€/MWh (the charge is started only when the imbalance price is negative).

As shown in Table 10, imbalance optimization revenues are further reduced by 61% compared to the case without threshold, while coupled DA and imbalance optimization revenue is reduced by 43%.

	Reduced availability	**Reduced availability + price thresholds**
Imbalance revenue [€/user.year]	283.16	111.51
DA + imbalance revenue [€/user.year]	312.81	179.16

Table 10: Imbalance and DA + imbalance revenue before and after the introduction of the price thresholds constraints. Imbalance optimization revenues are further reduced by 61% compared to the case without threshold, while coupled DA and imbalance optimization revenue is reduced by 43%.

6 Conclusion

This work investigated the potential value of EV residential charging flexibility in Belgian short-term electricity markets (Day-ahead, Intraday and imbalance markets).

First, a virtual fleet of 2000 users is generated. Each user is attributed a yearly set of trips, EV and charger specifications and charging habits with the aim of representing a realistic fleet for Belgium.

Secondly, the fleet charges are optimized following several strategies involving short-term markets. A mono-market approach is first presented, with the different nature and time scales of the markets implying different methodologies. Day-ahead optimization consists of completely redispatching the charges pattern to charge at the cheapest hours. The benefit of such an optimization lies in cost saving compared to a reference where the charge would not be optimized. On the other hand, intraday and imbalance optimizations start from an existing charging plan (the uncontrolled charging pattern in the mono-market approach) and generate revenue by occasionally deviating from this plan within a charging session to stop the charge (resell electricity) and restart the charge (rebuy electricity) whenever there are interesting opportunities in these markets. Given the different timescales of the markets, a coupled approach is also studied, with the possibility to first optimize the charges in DA and use this DA-optimized charging pattern for an optimization in the intraday and/or imbalance market.

The aforementioned optimizations have been implemented in the form of a linear programming model and executed for the year 2023. The results showed that the optimization coupling day-ahead and imbalance is the most financially profitable, generating an average annual revenue of €498.92 per user, with 40% of the value coming from the DA optimization and 60% from the following imbalance optimization. Results show a great variation between users with, for all optimizations, the number of kilometers travelled per year the most important factor influencing the income generated. Intensive drivers have greater energy needs and therefore more potential to shift this energy. Sufficient nominal charging power is however required to fully exploit this flexibility: for equivalent mileage, greater charging power generates greater value. This is all the more true for intensive riders where a low charging power rating appears as a limiting factor in the revenue generation: for users riding more than 20,000 km per year, those with low charging power rating (3.6 kW) generate on average 30% less value than those with high power rating (7.2, 11 or 22 kW) in the coupled DA and imbalance optimization. The battery capacity also has an impact on the revenues of some of the optimizations, albeit less significant than the nominal charging power.

These results must however be considered in light of the assumptions behind the optimization algorithms. Optimizations rely on perfect foresight and price-taker assumptions, i.e. prices are given and known in advance with perfect precision. It is also considered that EVs are always connected and available when they are at home. The revenue is computed from the retailer's point of view and thus represents the in-market gains rather than the potential savings of the consumer.

The assumption of total availability of the vehicle at home does not represent the current situation. In reality, users currently do not always plug in as soon as they are at home and cars are rather available around 25% of the time spent at home. To better represent the revenue potential with the current users' behavior, optimizations have been re-executed with a reduced availability: EVs are available for charging during off-peak hours and only when the user really intends to charge (i.e. when a charge is engaged in the uncontrolled case). Under this new assumption, DA optimization revenues are reduced by half, while revenues generated by the coupled DA and imbalance optimization are reduced by 37%, dropping from 498.92 to €312.91 per user. The new optimizations with regard to this reduced availability also showed that it was an important factor influencing revenue generation, with greater availability allowing greater flexibility. From the retailer's point of view, it could therefore be worth encouraging users to plug in more often so that the car is available to provide flexibility.

Moreover, the perfect foresight assumption brings results that are a maximal upper bound of the reality. If for the day-ahead optimization, this assumption is reasonable and we can argue that the reality lies not so far from this upper bound, it is more questionable for imbalance and intraday, where real optimization results could be far from this upper limit. It is therefore appropriate to be cautious with the revenue values resulting of intraday and imbalance optimization, but these optimizations nevertheless make it possible to identify that there is an interest in implementing coupled strategies and to understand the factors influencing user flexibility.

This study showed that smart charging in DA already enabled a significant reduction in costs, with a certain level of confidence in the underlying value, and that participating in the imbalance market was a good way of generating additional revenue, with less confidence in the values that are over-optimistic. The implementation of an imbalance optimization strategy relaxing the perfect foresight assumption would allow more realistic financial results to be obtained and is left as a suggestion for future work. Additional investigations may also include the integration of bi-directional charging capabilities in the optimization and an assessment of the potential value of EV residential charging flexibility in ancillary services.

Appendix A - EV fleet modelling: full report

A.1 Introduction

The relationship between human activities and climate change is well established, and drastic, immediate, and global action is required to avoid global warming exceeding 1.5°[1]. European Union aims to be carbon neutral by 2050 [2]. However, at present, 37% of European electricity production comes from fossil fuels. More globally, 70% of Europe's energy supply is still based on fossil fuels [3].

The transition of our energy systems towards decarbonised solutions is therefore a major challenge, and the electricity system in particular will face significant changes. The growing share of renewable energy sources (RES) in the electricity mix poses a problem of grid balancing. Electricity supply and demand must be equal at all times, and it is historically the supply that adapts to meet uncontrolled demand. As RES like wind and solar are not controllable, the grid balancing will require an action on the electricity demand [4].

On the other hand, the transportation sector must also face a transition towards decarbonised solutions and the European Union plans to ban Internal Combustion Engine vehicles by 2035 [5]. Electrical vehicles (EVs) are part of the solution and, although it represents a challenge to integrate their consumption in the grid functioning, this is also an opportunity to integrate them in the network operations. Even if there are no official statistics, it is acknowledged that cars spend 95% of their lifetime parked [53], and the time spent being parked is an opportunity to be used to provide flexibility to the network.

As part of my master's thesis, I will assess the value and the flexibility EVs home charging can bring in a Virtual Power Plant. To analyse when and how EVs can provide services to the network, we are interested in knowing information such as the state of the car (is the car riding, parked, charging, connected but not charging?), the power exchange and the state of charge (SoC) of the car every quarter-hour of the year (this is the resolution used in most markets and a good trade-off between computation time and sufficient precision).

In the literature, residential charging is still relatively unknown and we lack real charging data in Belgium, leading to the necessity of modelling residential charging in Belgium.

This report is the synthesis of the model developed to create a realistic fleet of EV users whether in terms of riding profile and charging behaviour. A small review will first be performed to examine the paper using real data from other countries that will be a basis to compare with the results of the model. The structure of the model will then be presented with its different parts which are the trips generator, the charge generator and the aggregator.

A.2 Real data paper review

A Norwegian study from 2021 analyses real charging sessions and provides all the used datasets online [11]. The case study is a housing cooperative with 2400 residents living in 1113 apartments in Trondheim, Norway. The garages of the housing cooperative offer charge points (CPs), both private and shared, and the charging sessions have been recorded from December 2018 to January 2020. The data are completely available online and explained in a separate paper [54].

The main limitation of this study is that the number of EV users is not constant with time during the measures, starting from zero in December 2018 to 82 in January 2020. This could limit the relevance of the results as the number of users at the beginning of the measures is low. Furthermore, the charging power is unknown. However, the available data provide the recording of 6 878 charging sessions registered by 97 different users and includes information such as plug-in time, plug-out time and energy charged for each session.

Shared charging points are outside the scope of our study and will not be taken into account when comparing the simulation results with the paper's results. This again reduces the number of usable data to a maximum of 53 users.

However, this document offers the advantage of providing all the datasets containing recorded charging sessions freely accessible online. This will be a basis to compare the results of the simulation with real-world data.

A.3 The model

Figure 33 represents a simplified diagram of the model structure. First, the trips generator creates, for each user, an annual set of trips with information such as departure/arrival time and the travelled distance. Then, the charges generator creates charges to fulfil the trips demand following a certain behaviour and generates a quarter-hourly dataset with information such as the SoC or power exchange. Then, the aggregator makes the sum of all EVs to analyse the fleet as a whole.

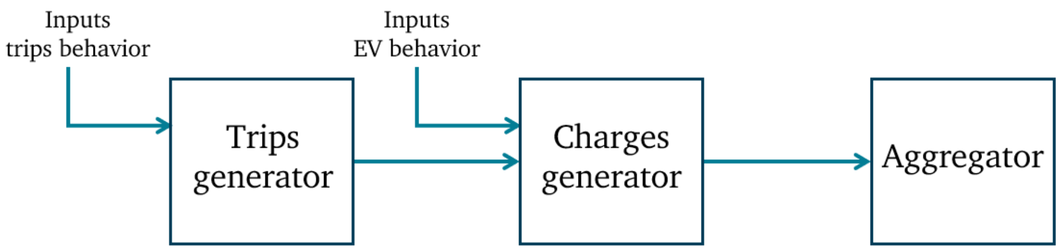


Figure 33: Simplified diagram of the model structure

A.3.1 The trips generator

The trips generator is inspired by a previous project developed at Engie Laborelec by Jelle Garcet and generates trip profiles based on probability distributions.

Those probability distributions are constructed using the Monitor survey [35], the last major mobility survey in Belgium. The survey is based on more than 10,000 respondents who were asked to complete a travel diary. On a given day, respondents were asked to provide details of all their journeys, their reasons for travelling and the modes of transport used. Cumulative

Distribution Functions (CDF) were created based on the survey results for departure time from home, arrival time to home and travelled distance. CDFs are created according to the region (Flanders, Wallonia and Brussels) and the travelling reason (categorised into 4 types: work, shopping, social and visit). As an example, Figure 34 shows the CDF used for departure time to work of a Flandrian.

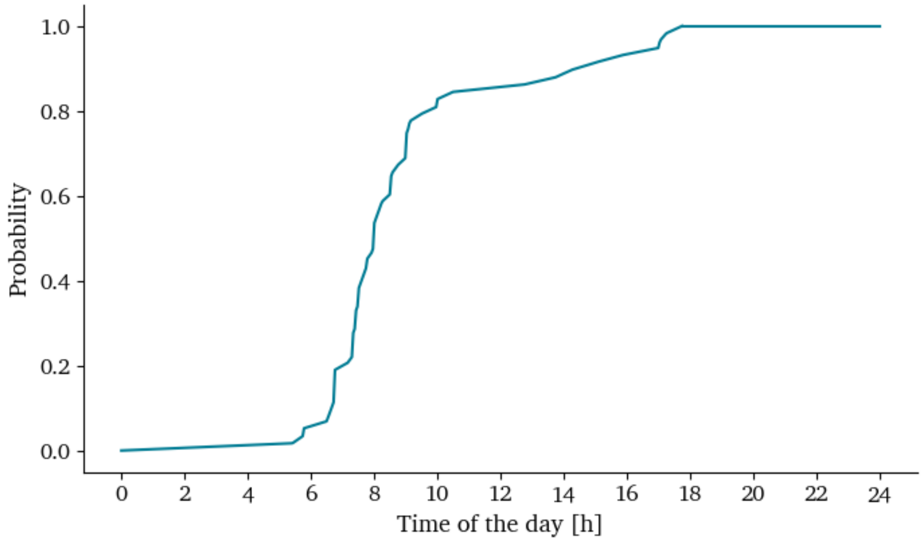


Figure 34: CDF of departure time to work for Flanders, created based on all the trips made by Flandrians to go to work in the Monitor survey.

The following subsections detail the inputs and assumptions that have been introduced into the trips generator.

- **EV users drive more than average**

In the former studies performed at Laborelec on the subject, the assumption that EVs are used in the same way the ICE cars was taken.

In Norway, according to the Norwegian Statistics Bureau, the mileage of EVs was 10% higher than that of all types of vehicles in 2020 and 16% higher in 2022. [47]. In Belgium, there is no systematic annual survey on the use of electric vehicles. However, we can find information in the annual report of the non-profit association Car-Pass [37], which fights against odometer fraud. Every time a car is in the hands of garages, tyre companies, technical inspections, or any professional making reparation or maintenance on cars, they have, by law, to forward the current odometer reading to Car-Pass. That allows them to have a good view of the annual mileage of the Belgian fleet. In their 2022 report, we can find that EVs rode 14.7% more (19000km against 16500km) than the average all types of fuel user (that is consistent with the numbers of Norway). Car-Pass explains this by the fact that most EVs in Belgium are very recent and are mainly company cars, which tend to be driven more. Another fact that could explain why EV users ride more than others is a kind of rebound effect due to the lower ecological impact of electrical vehicles which could increase the use of cars for short journeys.

However, it is important to note that the current situation in Belgium may not be an accurate representation of future trends. The Belgian EV fleet is currently composed primarily of company cars, which may have a bias on the estimated annual mileage for upcoming years when EVs become more widespread and represent the majority of the Belgian fleet.

A study about the charging habits of Engie clients owning EVs in France [55] does not go in the same direction as the statistics found for Belgium and Norway. In this survey with 800 EV owners where 94% of the respondents have personal cars and not company cars, it is said that small riders (less than 12000 km/year) are over-represented among EV owners and 18% of respondents declared riding less than they did before owning an EV.

In conclusion, the average annual mileage targeted in the trip generator is 19000km, bearing in mind that this represents the current Belgian situation, which will probably evolve in the future.

- **Probability to make a trip**

In the trips generators, the CDF for departure time, arrival time and distance for each type of trip have been described, but one point is missing: the probability of making a trip on a specific day for a specific reason (for example the probability to go to work on a weekday). The probabilities initially used in the trips generator did not allow the annual distance to be matched. Therefore, the probability of making a trip for work during weekday and for shopping and social during weekends have been boosted. In addition, the probability of going shopping and social during weekends was arbitrarily increased to be consistent with the Norwegian data and the traffic data analysed for Belgium (see next section).

Concerning the probability of going to work on a weekday, it has been modified according to statistics about teleworking and part-time jobs. A recent survey about teleworking in Belgium performed between October 2022 and May 2023 [36] (teleworking was no longer imposed due to sanitary reasons) stands that 33% of respondents do teleworking at least once a week. Among them, 67% are teleworking one or two days per week and 33% three days or more per week. Moreover, 26.1% of employees worked part-time, mostly 4 days over 5.

The population have been divided into 3 categories: people going to work 5 days over 5, 3 or 4 days over five and less than three days over five. The proportion of the population belonging to each category is shown in the Table 11, together with the associated probability used in the code every time a trip for work is created. As an example, every time a new user is created, there is 33.8% probability that this user go to work 3 or 4 days out of 5. For such a user, every weekday of the year, the probability of him going to his workplace is 70%.

Number of days of presence at work	Probability to go to work on weekday	Proportion of the population
5 days per week	0.95	49.6%
3-4 days per week	0.7	33.8%
<less than 3 days per week	0.4	16.6%

Table 11: Probability to go to work distribution. Each time a user is created, he is assigned to a population category, which will determine the probability of him going to his workplace on a weekday.

Figure 35 illustrates how the percentage of each part of the population has been computed. The population is first divided into full-time and part-time workers and then according to the number of teleworking days. The only category belonging to 5/5 working days is the full-time workers not teleworking (represented in dark blue in the figure, 67% of 74% is 49.6%). People working part-time and not teleworking, as well as people working full-time with 1 or 2 days teleworking belong to the 3-4/5 days at work category (represented in light blue in the figure, 67% of 26% plus 22.1% of 74% is 33.8%). The last possibilities belong to the <3/5 days at work category and are represented in white in the figure.

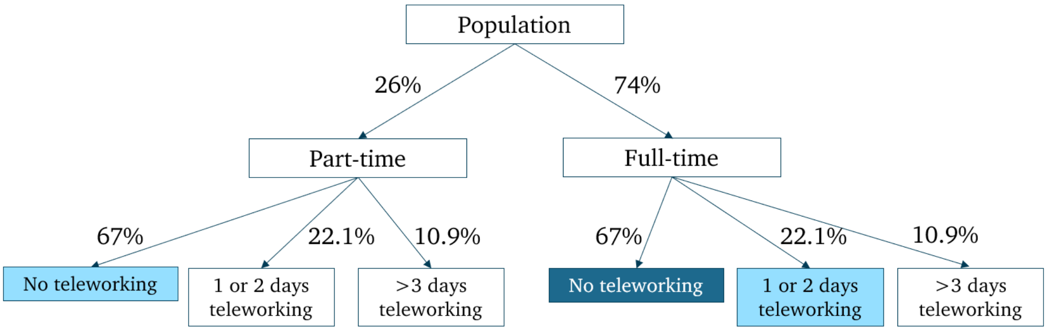


Figure 35: Distribution of the population according to teleworking and part-time work

- **Variation of traffic along the year**

The Norwegian paper showed a correlation between traffic along charging points and plug-in/plug-out times, as well as a reduction in the total energy charged during holidays [11], and it is reasonable to assume that the more traffic there is, the more energy will be needed and charged on a global fleet point of view.

To analyze the effect of holidays on the total energy charged, traffic data for Belgium have thus been gathered via the Telraam project, which is a participatory traffic counting tool developed with the support of Smart Mobility Belgium fund [56]. The Telraam sensor is placed on citizens' windows and counts and classifies road users, providing anonymous, aggregate data per traffic mode and direction with a 15-minute resolution [57]. Collected data can then be shared with local authorities and policymakers as Open Data and are accessible online through their API.

Hourly counts of cars have been gathered for Belgium in 2022 with an hour resolution. As the number of active sensors changes throughout the year, results were normalised by dividing by the number of active segments (roads where measurements are taken) each hour. It is important to note that in its current version, the sensor can only count cars during daytime, as the counting tool is based on a camera that does not perform well in obscurity. It would therefore be irrelevant to count the total volume of cars to analyse variations from one month to another, given that sunrise and sunset times vary considerably throughout the year.

As the total volume cannot be computed for every month, the instantaneous number of cars at peak hour is analyzed instead. Figure 36 shows the variation in the average number of cars at peak time by month. The reduction in traffic due to the summer holidays is visible in July and August, with a 23% reduction in traffic compared with the average of the other months. To take into account this reduction of traffic in the trips generator, a probability that users go on holiday has been introduced. Assuming that each user goes on holiday on average one or two weeks over the 8 weeks of July and August, there is in the trips generator an 18.75% chance that users go on holiday each summer week. If it is decided that the user is on holiday, all the trips of that specific week are discarded and the car is considered unavailable from the point of view of the house.

Traffic analysis also showed a reduction of traffic for bank holidays falling on weekdays, with traffic curves similar to those of Sundays. This has been taken into account in the trips generator by saying that bank holidays are considered as Sundays in terms of probability of making a trip for a certain reason.

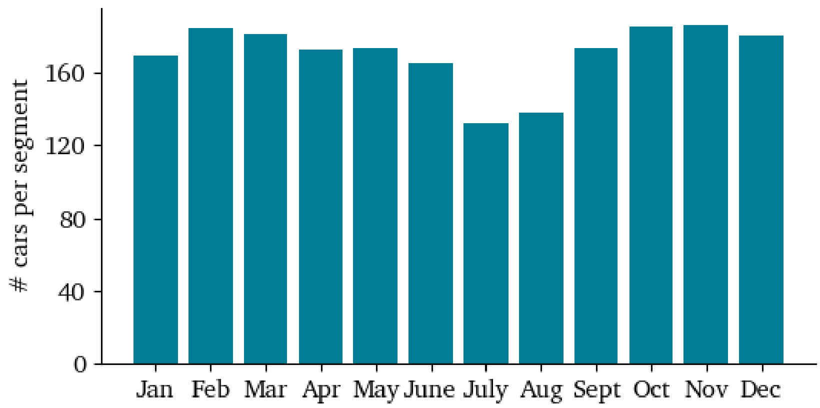


Figure 36: Average cars per segment at peak time - by month. The peak traffic is reduced by 23% in July and August compared to the average of the other months

A.3.2 The charges generator

The output of the trips generator is the list of all trips of the year with departure time from home, arrival time to home and distance for each user. Based on those trips, the charges generator creates the charges that meet the displacement demand following a certain behaviour. Two *uncontrolled* (the charge starts right after the user connects the EV to the charger) behaviours have been identified and used in other models [38] [39]:

- *Top-up charging*: user always starts charging when back home, regardless of the SoC.
- *Soc charging*: user only starts charging when back home if the SoC is beneath a certain threshold.

Batteries are charged until 80% to extend the lifetime of the battery, in accordance with the literature [40] and the manufacturer's advice, but it is allowed to charge occasionally to 100% if needed for the next trip. A charge is also engaged if the SoC is below 20% or if the energy contained in the battery is not sufficient for the next journey, even if this is not in line with the main charging logic.

As all the trips are generated before the charges, it is not guaranteed that the charges succeed in fulfilling the trips demand. For example, for two trips that are close in time, the car may not have enough time to load the desired quantity. To avoid unrealistic cases leading to a car riding with a null SoC, the evolution of the SoC is checked a posteriori. If the car rides with a null SoC less than 5 times in the year, the problematic trips are just discarded and the charges regenerated. If the car rides with a null SoC more than 5 times in the year, the combination of riding and charging profile is considered incompatible (for example a user that rides long distances every day to go to work with a low-range battery and/or a low power charger). In this case, trips are regenerated with the same profile characteristics but a smaller average annual distance, then the charges are regenerated based on this new set of trips.

The following subsections detail the inputs and assumptions that have been introduced into the charges generator.

- **Proportion of energy charged at home:**

In the Norwegian study, users charged on average for 10 700km on their residential CP. Knowing that the average annual mileage of EVs in Norway was 12631km the year of the study (2019) [47], we can estimate that they charged 84.7% of their energy at home. The Enedis annual survey for France says that 85% of respondents use residential CP as the principal source of charging [58]. Although this says nothing about the proportion of energy charged at home, it does indicate the extent of use of residential CPs. The National Charge Survey 2022 from the Netherlands stands that the EV drivers owning residential CP charge 77% of their kilometres at home [59].

Based on these statistics for other countries, it has been assumed that 80% of kilometres are charged at home. As the algorithm only sees the moment the car is at home, it was difficult to implement charges in between. To take this into account, the number of kilometres has been artificially reduced to represent that all kilometres are not charged at home. The average annual distance to be matched has then been reduced by 20% (from 19 000km to ≈ 15 200km). There are several manners to reduce the annual distance: reduce the distance of trips, reduce the probability of making a trip or suppress a posteriori one trip over five. If we suppress trips, the car will be seen by the house as more available, but that is not what we want to represent as the charges made outside the house are made when the car is seen as riding. Reducing the probability of making trips would lead to the same bias. Reducing trip distances appears to be the most appropriate way of achieving this. An arbitral reduction of distances by 10% allowed us to obtain an average annual distance around the desired one.

- **EVs and chargers characteristics:**

As EVs do not yet represent a significant proportion of vehicles in Belgium, it is difficult to obtain information on the composition of the EV fleet. Based on top sales from recent years [43, 44, 45], Table 12 shows how the fleet has been divided, according to battery capacity (low, medium, long and very long range) and electricity consumption (berlines and SUV). The electricity consumption indicated in the table is the consumption at optimal conditions (temperature of 20°C and no use of air conditioning [46]).

Category		Consumption [Wh/km]	Battery capacity [kWh]	Proportion
Low range		140	39	20%
Mid range		140	57.5	30%
Long range	SUV	165	75	20%
	Berlines	140		20%
Very long range	SUV	175	95	5%
	Berlines	140		5%

Table 12: EV fleet distribution. Each time a user is created, it is assigned to a category according to the probabilities indicated in the Proportion column and the corresponding parameters are assigned to it.

Concerning the charging points, no information about the nominal power of residential charging points has been found for Belgium. The assumed distribution is shown in Table 13. Charging power is assumed constant with a charging efficiency of 90%.

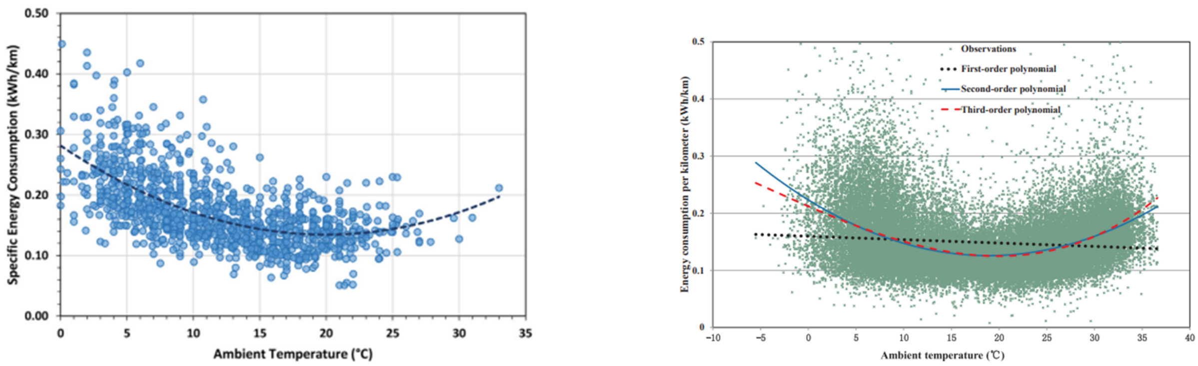
Charging power [kW]	3.6	7.4	11	22
Proportion [%]	30%	50%	10%	10%

Table 13: Charging power distribution

- **Effect of temperature:**

Several factors influence EV electricity consumption, such as traffic conditions, speed driving behaviour or environmental conditions. As far as environmental conditions are concerned, ambient temperature is considered to have a significant impact, mainly because of the consumption of auxiliary cooling or heating devices, the increase in air density at low temperatures leading to greater air resistance and the reduction in battery efficiency [41]. Figure 37 shows how the electrical consumption varies with temperature in real driving conditions [41, 42]. We can clearly identify a "*U shape*" with minimal consumption around 20°C.

From Figure 37b, a multiplication factor has been constructed. This factor is shown in Figure 38 and multiplies the optimal consumption indicated in Table 12, depending on the temperature while riding. Figure 37b was preferred over Figure 37a because, although it is older, it covers more measurements from different EVs.



(a) Real measures obtained from a Nissan Leaf in UK from Jan. 2016 to Sept. 2019 [41]

(b) Real measures obtained from 68 EVs in Japan from Feb. 2011 to Jan. 2013 [42]

Figure 37: Energy consumption in function of the ambient temperature - Real measurements.

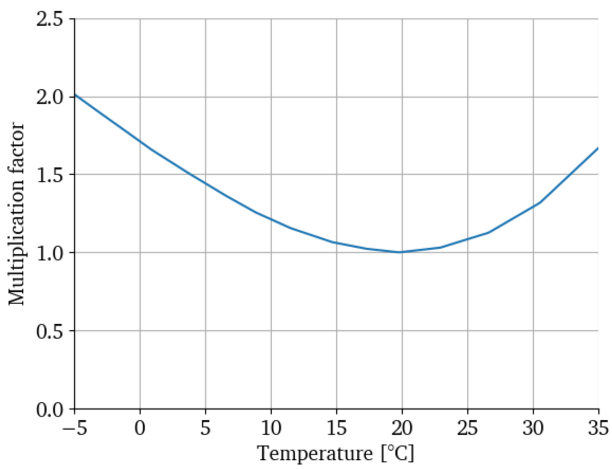


Figure 38: Synthetic multiplication factor constructed on the basis of Figure 37b. Electricity consumption is optimal around 20°C and increases sharply for colder or warmer temperatures, doubling at -5°C.

A.3.3 The aggregator

As its name suggests, the aggregator simply makes the aggregation of all users to analyse them as a whole and to have a view of the global SoC, available capacity and power exchange of the fleet at each quarter hour of the year.

The aggregation already allows us to draw some results. Figure 39 shows the aggregated weekly average demand, normalised by the number of users. The peak consumption appears when people return from work and the total demand is substantially reduced during weekends. Figure 40 shows the percentage of users that are available during an average week. Cars parked at home, connected but not charging and charging are considered to be available for charging. The percentage of available users is high during the night, almost reaching 100% and low during the day when people are at work. Weekends show a greater availability than weekdays.

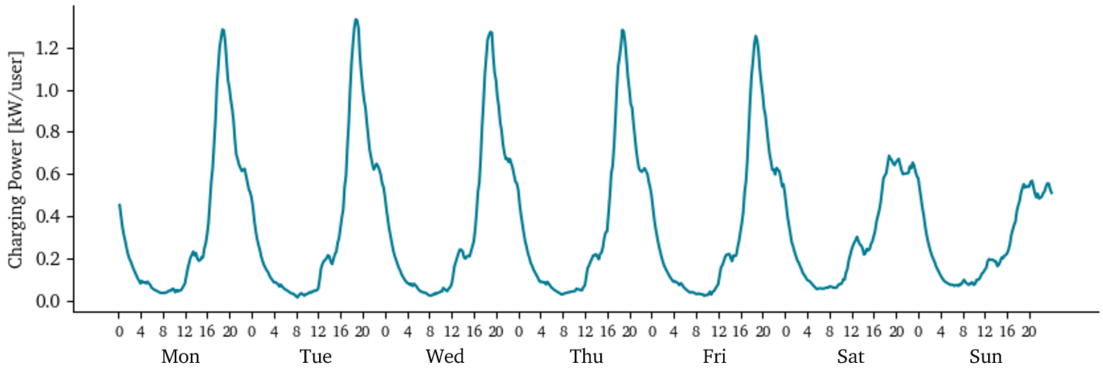


Figure 39: Weekly average demand profile. The power demand reaches a peak in the early evening and rapidly decreases in the night to reach the lowest point in the morning. Demand is substantially reduced during weekends.

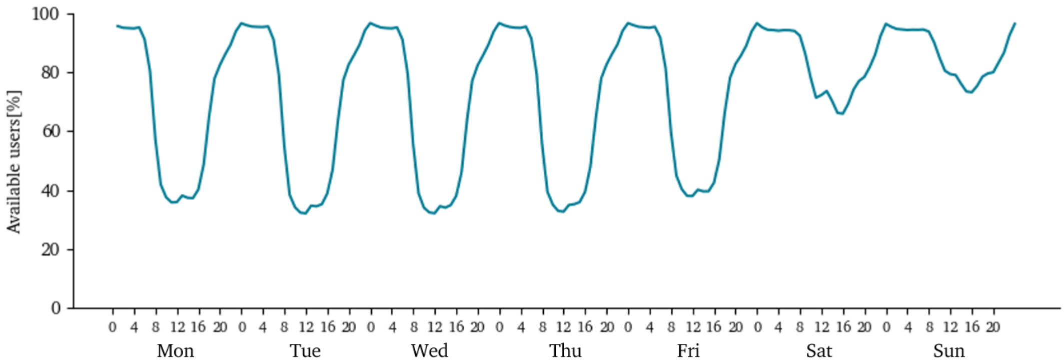


Figure 40: Weekly average users availability. The percentage of available users is high during the night, almost reaching 100% and low during the day when people are at work.

Figure 41 shows the total energy demand for charging by month, normalised by the number of users. It can be observed that 72% more energy is charged during January and December compared to July and Augustus. This is because January and December are the coldest months of the year, and the reduction of demand due to summer holidays further accentuates this difference.

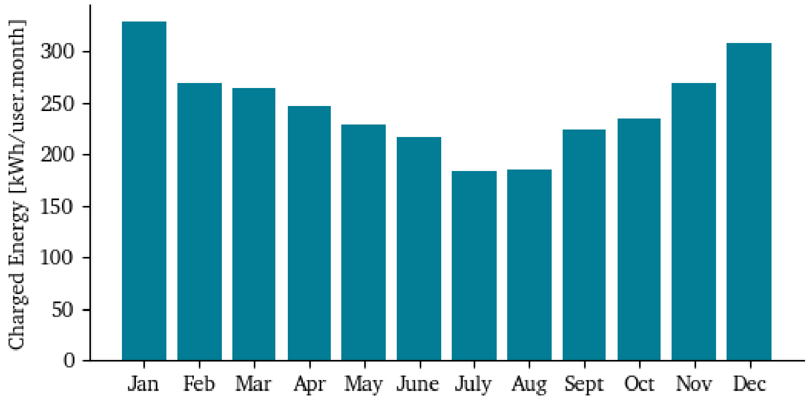


Figure 41: The monthly energy demand shows great variation between summer and winter months due to temperature and summer holidays effect, with 72% more energy charged during January and December compared to July and Augustus.

A.4 Comparison with real data

Waiting for the possibility to confront the model to real Belgian data, results have been compared with the available data from the Norwegian paper [11]. The data available comes from Norway, with a limited number of users that varies over the year (the number of users with a personal CP rises from zero to 68 over the measurement period). The relevance of this comparison is thus relative, but it nevertheless does allow the model to be compared with real-world data.

Because of this wide variation in the number of active users, analysing the variation along the year is difficult, but the paper provides a freely accessible dataset with all the recorded charging sessions and information such as plug-in time, plug-out time and energy charged by session that allows an in-depth analyse of the charging sessions. Different metrics have been defined to compare the simulation fleet to the Norwegian data:

- the average amount of kilowatt-hours charged per session, as well as the standard deviation
- the average amount of kilowatt-hours charged per week
- the number of charges per week
- the percentage of charges starting on a weekday, Saturday or Sunday
- the percentage of charge starting at night (0am to 6am), in the morning (6am to noon), in the early afternoon (noon to 3pm), in the late afternoon (3pm to 6pm) and in the evening (6pm to midnight).

Table 14 indicates the cited metrics for both the Norwegian data and simulation results. It can be observed that the simulation results are fairly consistent with the Norwegian data. The only notable differences concern the amount of energy charged per session and per week, which is higher in the simulation as we ride 50% more km in Belgium than in Norway [37, 47], and the percentage of charges starting during weekends. In Norway, more charges start on Sundays than on Saturdays while it is the opposite in the simulation. This is consistent with the traffic data collected for Belgium with more traffic on Saturdays than Sundays, whereas in Norway, there is a tradition pointed in the paper of going hiking on Sundays that might lead to supplementary displacements [60].

	Norway study	Simulation
Avg kWh/charge	11.61 kWh	15.20 kWh
Std KWh/charge	0.47	0.57
Avg kWh/week	42.71 kWh	50.20 kWh
N_charge/week	3.65	3.30
% charge_weekday	73.65%	74.11%
% charge_saturday	11.81%	14.24%
% charge_sunday	14.54%	11.65%
% charge_night	2.3%	1.20%
% charge_morning	6.9%	6.63%
% charge_early_aft	13.45%	10.07%
% charge_late_aft	34.6%	34.52%
% charge_evening	42.6%	46.57%

Table 14: Comparison between real Norwegian data and simulation results.

Figures 13, 14, 15, 16 in subsection 4.1 depict histograms displaying the distribution of plug-in and plug-out times throughout the day, for both weekdays and weekends, as well as for both the Norwegian data and the simulation results. The simulation results exhibit similar patterns to those observed in the Norwegian data, in both shape and magnitude. As expected, there is a high peak of plug-out in the morning when people leave for work, and a high peak of plug-in when they return home from work.

A.5 Impact of the fleet size

Previous results have been computed with a fleet size of 200 users to limit the computational time of simulations. Given the number of input parameters randomly chosen according to probabilities, this is probably not sufficient to cover all the possible combinations, i.e. if we run the simulation several times with 200 users, we will not obtain the same results. Table 15 shows three outputs of three different runs performed with 200 users. The average annual mileage is an output of the trips generator and is thus a good representation of how the results of the trips generator can vary from one run to another. The average amount of energy charged per week is an output of the charge generator and therefore contains the effect of all the input parameters. To show that even the convergence of the input parameters may not be guaranteed with a low number of users, the average battery capacity is also shown.

	Run 1	Run 2	Run 3
Avg annual mileage [km/year]	14 030	15 409	15 371
Avg energy charged [kWh/week]	48.09	52.35	51.93
Avg battery capacity [kWh]	64.93	65.53	65.10

Table 15: Comparison of outputs of 3 different runs with 200 users.

It can be noted that the results vary substantially, with a difference of 1400 km and 4 kWh between run 1 and run 2 for annual mileage and energy charged per week, which is not insignificant multiplied by the number of users.

Even the average battery capacity, which is 'simply' a parameter, is not stable with 200 users. Each time a user is created, the battery capacity is chosen between [39, 57.5, 75, 95] kWh with a probability [0.2, 0.3, 0.4, 0.1]. If we generate an infinity of cars, the average battery capacity would thus tend to be 64.55 kWh. Figure 42 shows the average battery capacity of a fleet of up to 5000 users, generated three times. This illustrates that 200 users are certainly not enough to obtain similar results from one simulation to another, but also that even with 5000 users, the convergence value is still not reached, even though we are only looking at the convergence of a single input parameter and not the output of the model, which takes a tenth of such inputs.

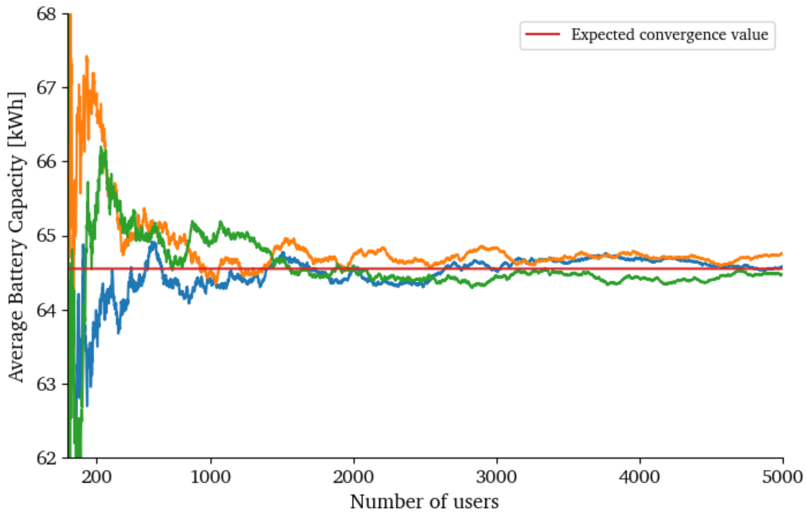


Figure 42: Comparison of the average battery capacity in function of the number of users for three different runs. At 200 users, the number of users initially used in the simulation, the battery capacity can vary widely from one run to another.

Looking further at the whole model simulation, the average quantity of energy charged per week is, as mentioned earlier, a good indicator of the model output as it contains the effects of all the input parameters. Simulations have been performed for 10, 100, 200, 400, 800, 1600 and 2000 users and the average energy charged per week is shown in Figure 43. As the results can widely differ with a low number of users, it is important to note that a scatterplot representation with several runs for each number of users would be more appropriate. Here, the choice has been made to link the points together to illustrate convergence, but for a small number of users, this is not representative of the variety of results that could be obtained. We can still conclude that 200 users is not enough to obtain stable results from one run to the next, while 2000 users already seem better, and going beyond would increase the calculation time too much anyway.

The average annual mileage follows the same trend as illustrated in Figure 44, but it is interesting to note that the average seems to converge towards ± 14 500 km, which is below the target of 15 200 km defined in subsubsection A.3.2 and shown in red in the Figure. This would not have been noticed with simulations counting 200 users. As a reminder, a reduction of the distances of 10% compared to the initial distances of the Monitor survey was applied to take into account that all the energy is not charged at home. This reduction has now been updated to be 5% to converge to the right target, but it has not been tested again with 2000 users given the high computational time.

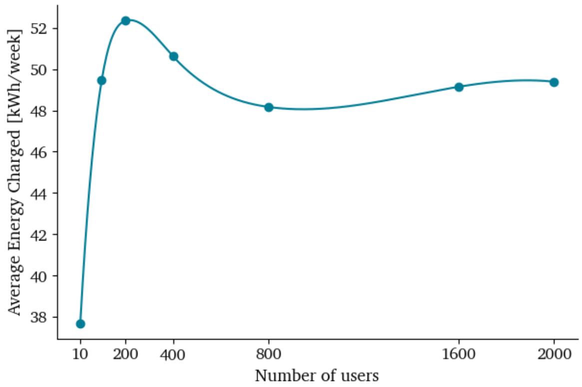


Figure 43: Average energy charged per week, for different numbers of users. Convergence towards 49.5 kWh

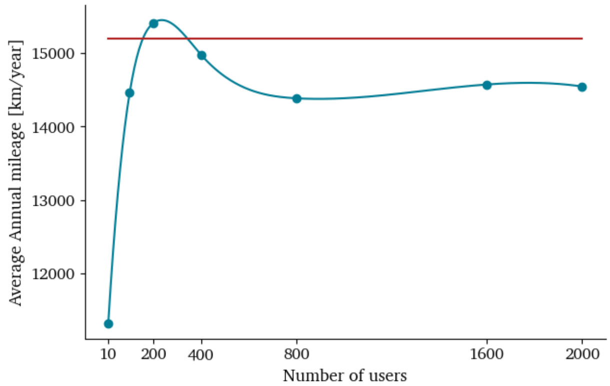


Figure 44: Average annual mileage, for different numbers of users. Convergence towards 14 500 km*, which is below the target.*

A.6 Conclusion

This work aimed to fill the gap of knowledge about residential charging in Belgium due to the lack of real data by providing a model which is intended to be as representative as possible, both in terms of charging and driving behaviour.

First, based on previous work developed at Laborelec and on statistical studies, trips profiles were generated. The trips generator generates sets of trips taking into account teleworking and traffic reduction due to summer or bank holidays. It has also been found that EV drivers currently drive more km than the average in Belgium.

Then, charging patterns have been created, taking into account the assumption that 80% of the energy is charged at home, typical battery capacities and charging powers and the effect of the ambient temperature on the electrical consumption. The peak power demand has been found to be on average 1.3 kW per user on a weekday, occurring between 6 and 7pm. The energy demand is on average 2700 kWh per user and year, but is not uniformly distributed throughout the year: due to temperature and holiday effect, 72% more energy is charged during January and December compared to July and Augustus.

The model has been compared to the real Norwegian data showing similar results in the observed metrics. However, we are waiting for the opportunity to compare the results with Belgian data, particularly the big difference in the energy demand between winter and summer months that might be surprising or greater than expected.

Given the number of statistics and assumptions used in the input parameters, it would be a worthwhile additional task to carry out a sensitivity analysis to study the impact of variations in the input parameters on the model. I have thought about performing Monte Carlo type sensitivity analyses, but the time and complexity required appear to be beyond the scope of this work.

Further analysis showed that the initial number of users used to run the simulation (200 users) was not sufficient to ensure that the results actually represented what the input parameters were intended to imply. It would in fact require several tens of thousands of users to converge to a perfectly stable output, but given the high computational costs, it has been limited to 2000 users.

Appendix B - Random Forest Regressor

The random forest regressor is an ensemble learning method that combines the output of several decision trees to improve accuracy and reduce overfitting [52].

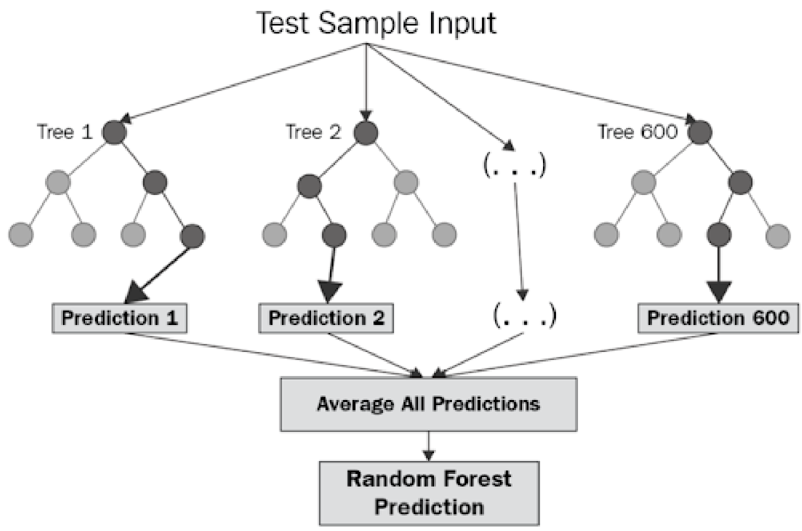


Figure 45: Random Forest Regressor (source of the Figure: [61])

It is a supervised learning technique where each decision tree is built from randomly sampled input features and data. A decision tree is constructed as follows: at each node, the algorithm selects a feature and a threshold that best separates the dataset into two subsets. The node is divided into two child nodes based on the selected feature and threshold. This process is repeated recursively for each child node until a stopping criterion is met. The prediction of each tree is then aggregated to obtain the final prediciton.

A built-in attribute of the regressor allows the identification of the most important input features with respect to the predictability of the target variable. The basic idea is that the more a feature is used to split the data in the decision tree, the more the feature is important. The use of the Random Forrest Regressor allows capturing more complex relationships between features and targets, as well as interactions or combined effects that would not appear in a simple linear correlation.

For each optimization and for each analyzed output, a Random Forest Regression has been applied using the scikit-learn python library, with the input feature listed in subsection 4.5. Strongly correlated input features are removed from the analysis. For example, the average kilowatt-hours charged per session and the number of charges per week are linked to user behavior, determined by the SoC threshold parameter. Only this parameter is therefore conserved in the feature importance analysis.

The following figures show the importance of features analysis results for DA and imbalance.

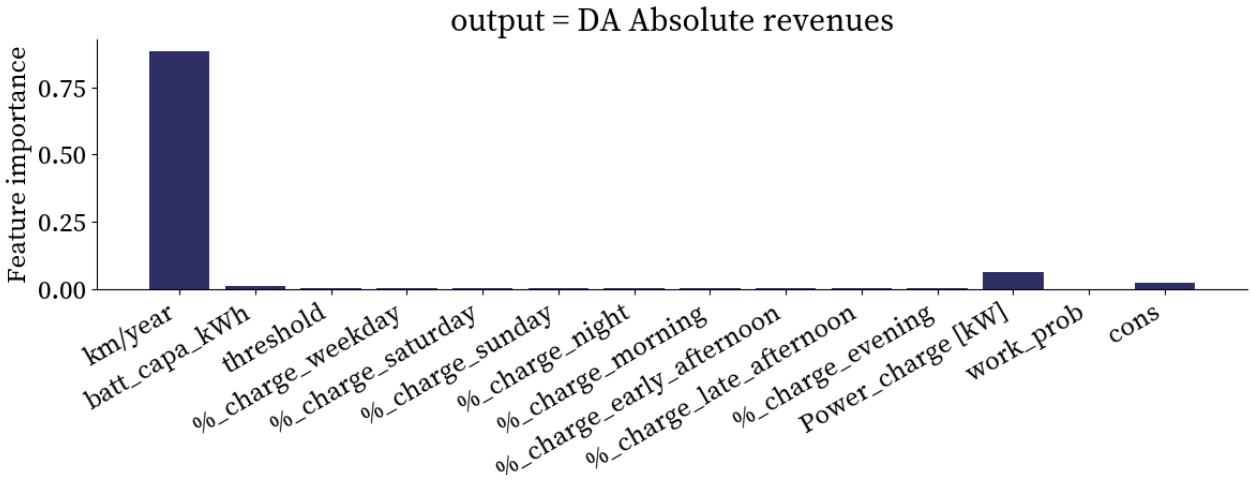


Figure 46: Feature importance results: DA opt. absolute revenues

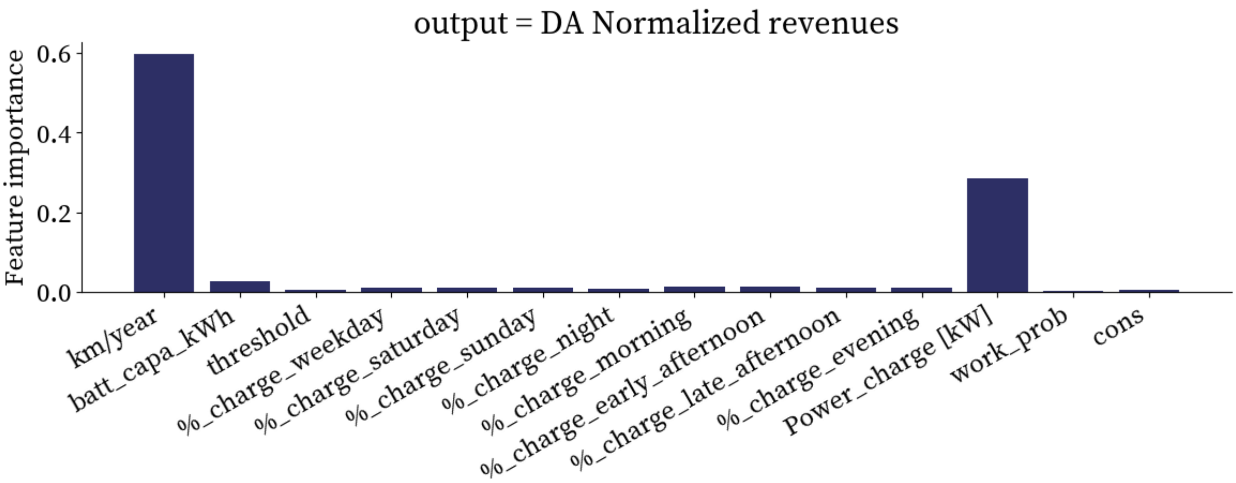


Figure 47: Feature importance results: DA opt. normalized revenues

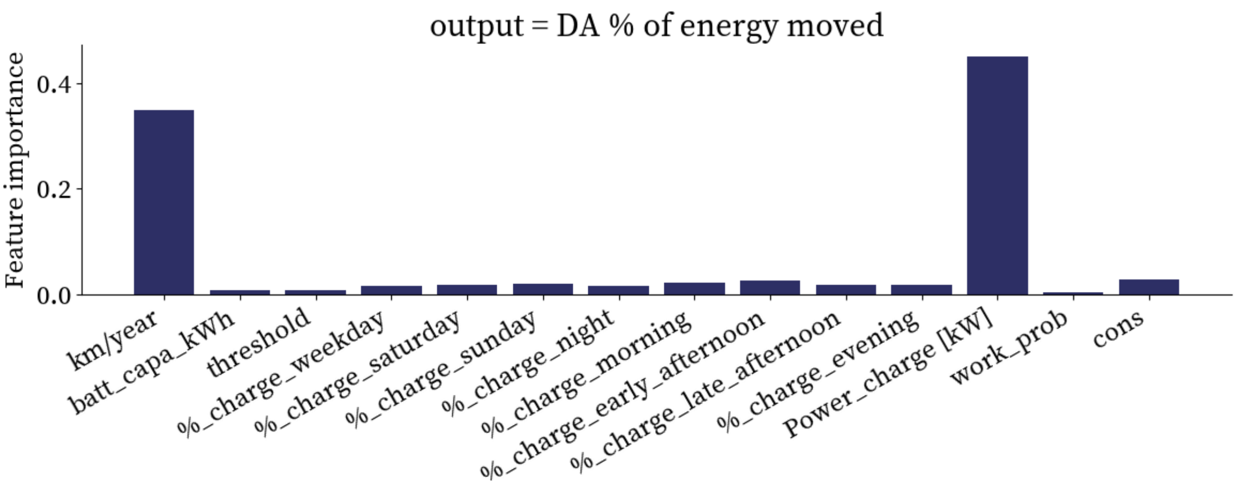


Figure 48: Feature importance results: DA opt. energy moved

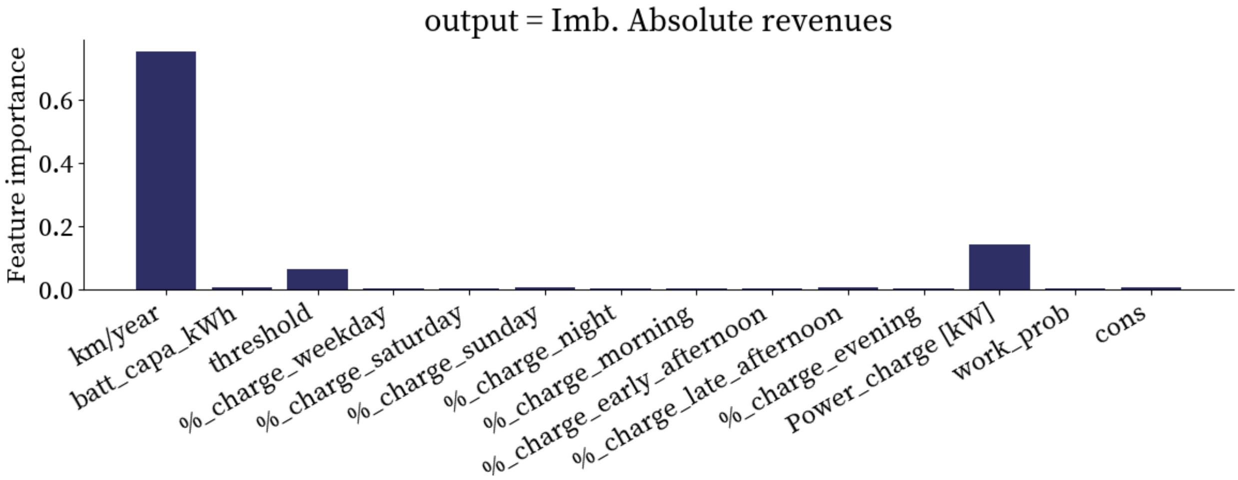


Figure 49: Feature importance results: Imbalance opt. absolute revenues

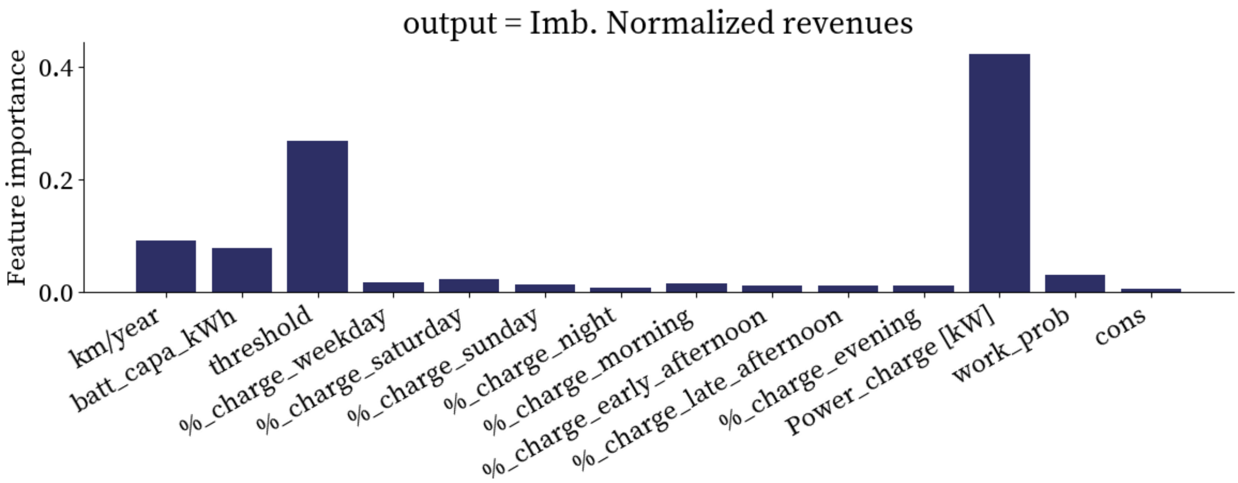


Figure 50: Feature importance results: Imbalance opt. normalized revenue

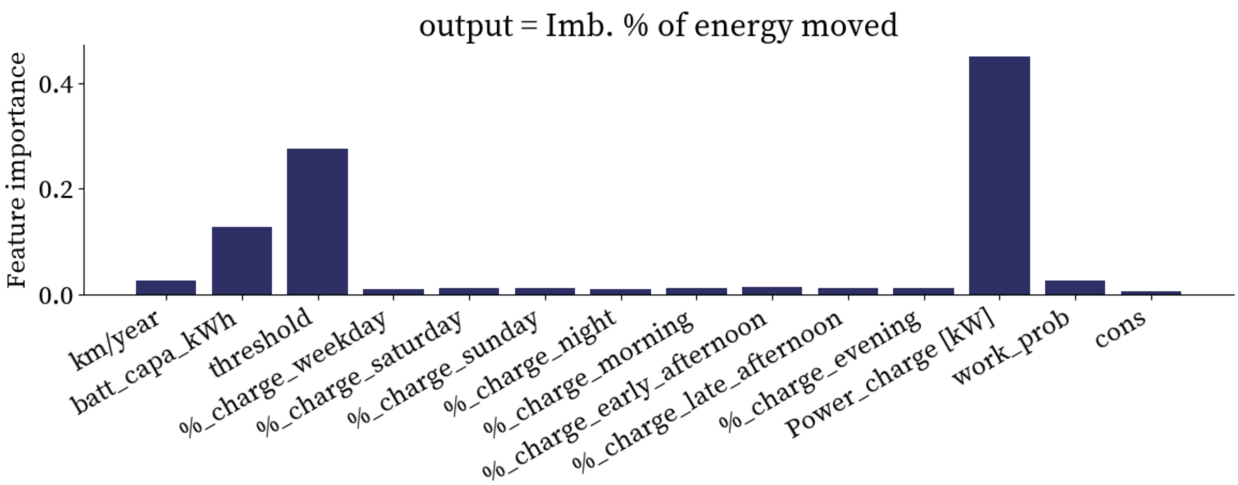


Figure 51: Feature importance results: Imbalance opt. energy moved

Appendix C - Additional results

C.1 Intraday optimization

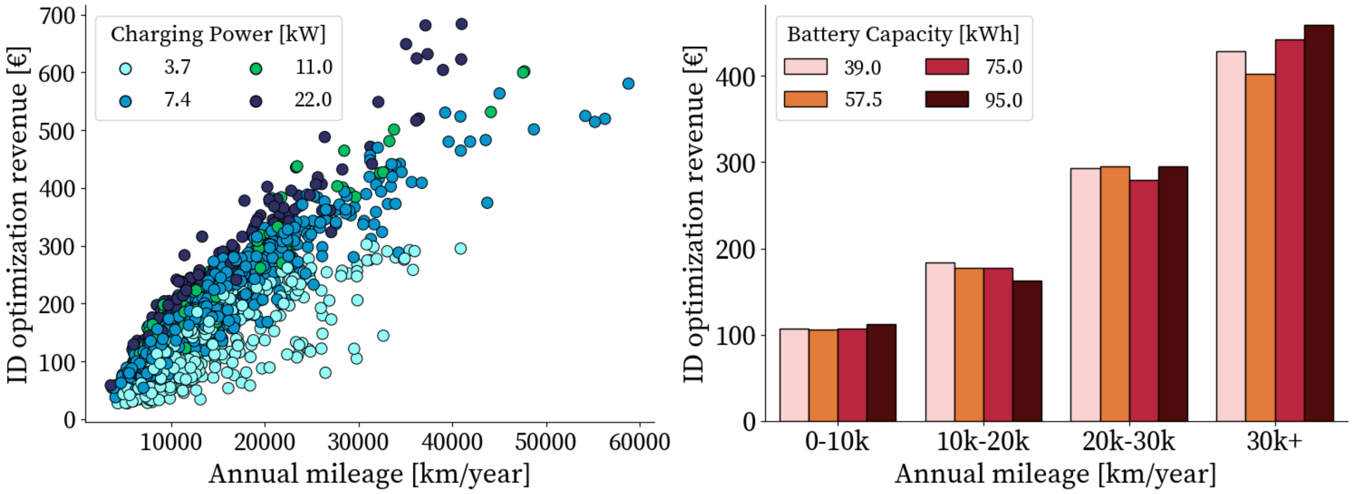


Figure 52: Intraday optimization revenue in function of the annual mileage. The revenue is directly correlated with the number of kilometers travelled by year. For equivalent mileage, a greater charging power rating generates more value (left). No tendency depending on battery capacity can be observed (right).

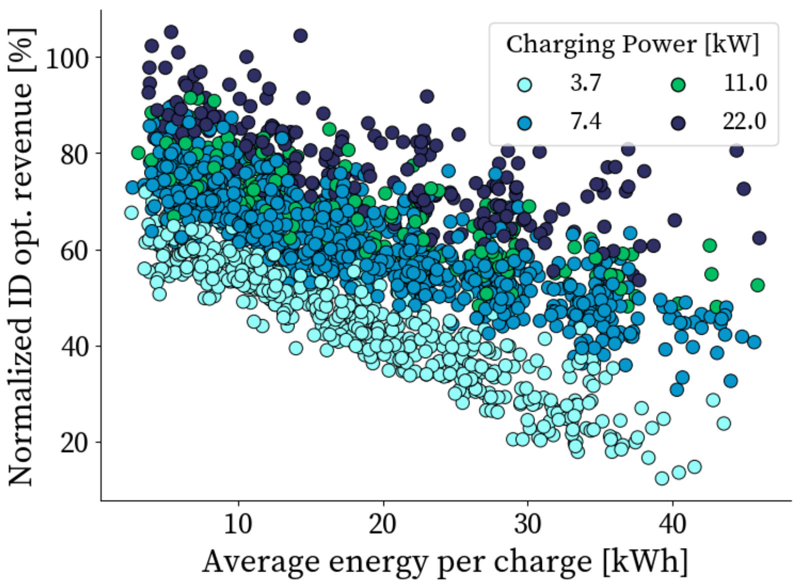


Figure 53: Normalized ID optimization revenue (expressed in percentage of the initial charging cost) decreases as the user charges on average more energy per session. A greater power increases the normalized revenue.

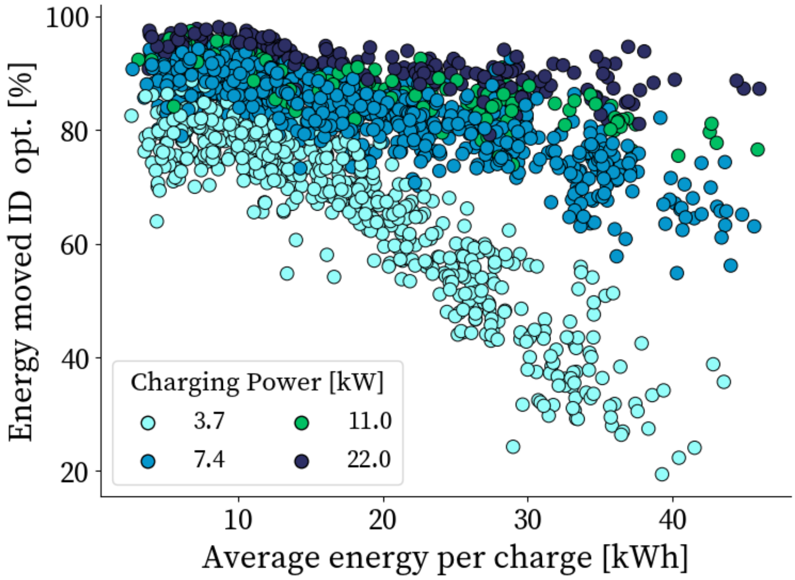


Figure 54: Energy shifting potential decreases as the user charges on average more energy per session. Higher charging power rating allows to move more energy.

C.2 Day-ahead and imbalance optimization

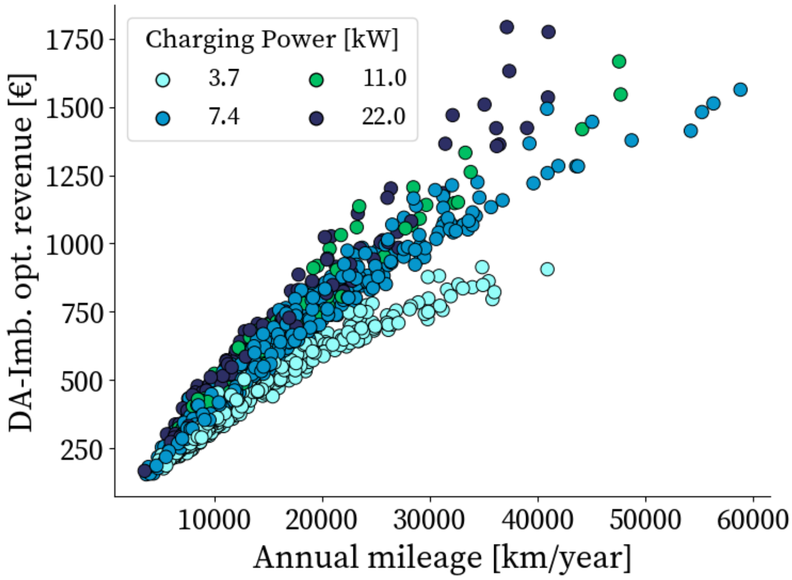


Figure 55: Coupled DA and imb. optimization revenue in function of the annual mileage. The revenue is directly correlated with the number of kilometers travelled by year. For equivalent mileage, greater charging power rating generates more value.

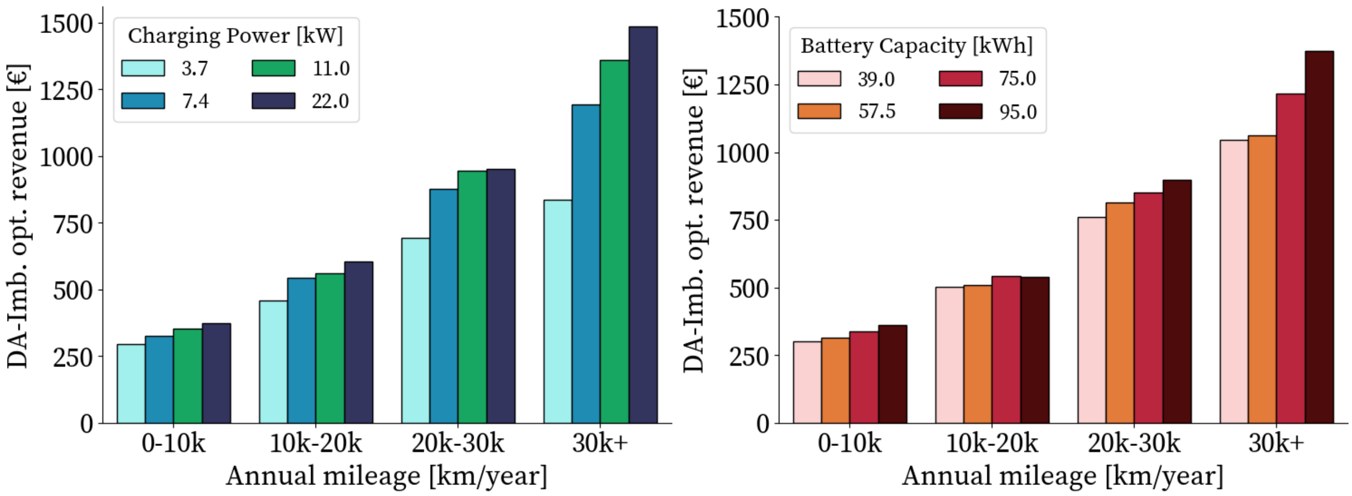


Figure 56: DA-imbalance optimization revenue in function of the annual mileage. The revenue is directly correlated with the number of kilometers travelled by year. For equivalent mileage, greater charging power rating generates more value (left), as well as greater battery capacity (right).

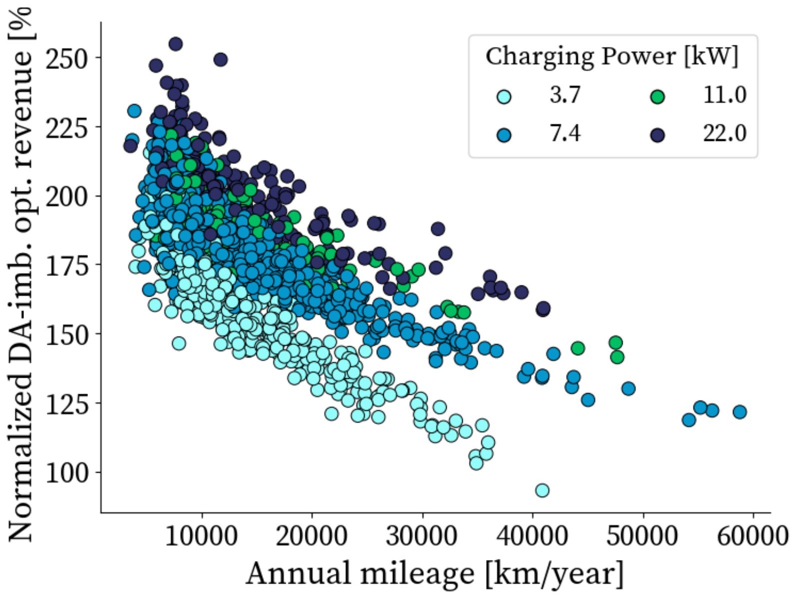


Figure 57: Normalized ID optimization revenue (expressed in percentage of the initial charging cost) decreases as the user charges on average more energy per session. A greater power increases the normalized revenue.

C.3 Coupled optimization

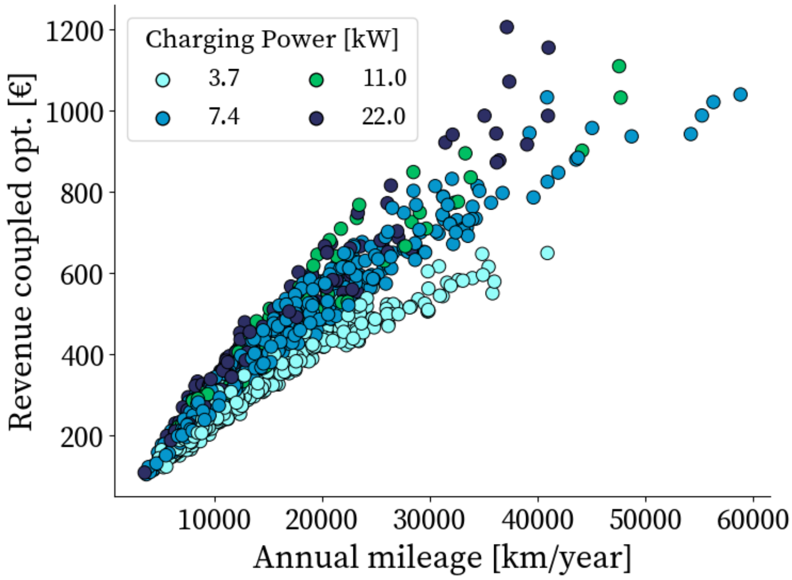


Figure 58: Coupled optimization revenue in function of the annual mileage. The revenue is directly correlated with the number of kilometers travelled by year. For equivalent mileage, greater charging power rating generates more value.

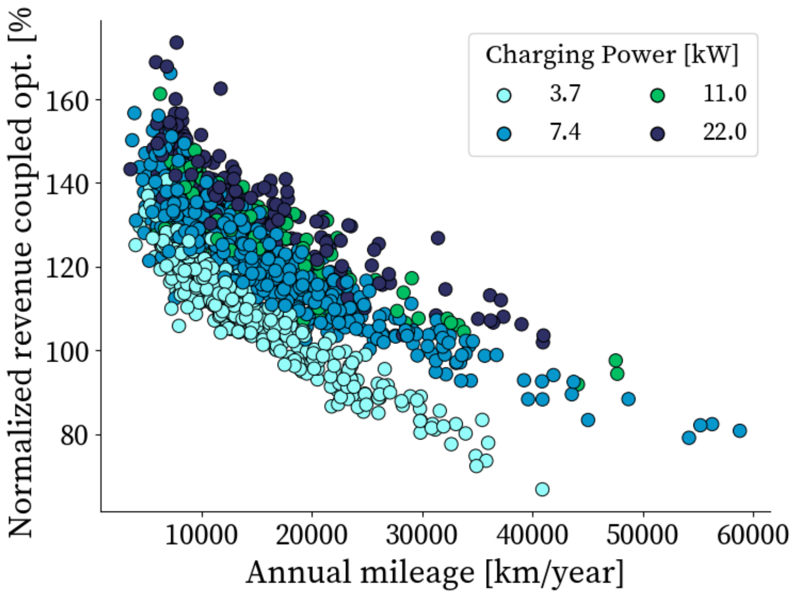


Figure 59: Normalized ID optimization revenue (expressed in percentage of the initial charging cost) decreases as the user charges on average more energy per session. A greater power increases the normalized revenue.

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